Essays on rational asset pricing

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Preface

Parts of the research reported in this dissertation are written in cooperation with others. Chapters 2 and 4 are written with Frans de Roon. Chapter 3 is based on a paper with Rob van den Goorbergh, Theo Nijman and Frans de Roon. Chapter 5 originated from joint work with Jenke Ter Horst and Chris Veld.

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Marta Szymanowska
Tilburg, August 2006

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Chapter 1

Introduction

This thesis consists of four essays that deal with rational asset pricing. If agents have rational expectations,[1] the most fundamental asset pricing equation states that there exists a pricing kernel or stochastic discount factor m_{t+1} such that for the excess return $r_{i,t+1}$ on any asset or security, we have

$$E_t\left[m_{t+1} r_{i,t+1}\right] = 0, \tag{1.1}$$

i.e., the *conditional* expectation of the excess returns multiplied by the stochastic discount factor equals zero. One way to interpret this stochastic discount factor is to think that m_{t+1} generalizes the standard discounting idea, i.e. it incorporates all risk corrections into one variable, and the asset specific corrections are generated by the covariance between the random component of this common stochastic discount factor and asset specific payoff. Another interpretation of the pricing kernel is that it is the marginal utility of the investor, i.e. m_{t+1} measures the rate at which investors are willing to trade consumption at time t for consumption at time $t+1$.

Equation (1.1) implies that the expected excess return on any security or asset depends on the covariance of the security return with the pricing kernel

$$E_t\left[r_{i,t+1}\right] = -\frac{Cov_t\left[r_{i,t+1}, m_{t+1}\right]}{E_t\left[m_{t+1}\right]}. \tag{1.2}$$

The expected return on any security or the risk premium is larger, the more negative is the covariance of a security return with the pricing kernel. Such assets deliver low returns in bad states of the economy, hence investors require more compensation for holding them. On the contrary, investors desire securities that deliver high payoffs in

[1] Assuming markets are frictionless and the law of one price holds.

these bad states. This means that investors prefer assets that covary positively with the pricing kernel and such assets will have lower expected returns or risk premiums.

The first essay of this thesis: *Consumption Risk and Expected Futures Returns,* focuses on the unconditional and conditional implications of Equation (1.1) and applies them to the cross-section of expected futures returns. Understanding these futures returns, whose expectations basically reflect risk premia, is important for academics studying asset pricing models as well as for practitioners, since they are important input variables for portfolio and risk management models e.g. More specifically, in this essay we focus on a relation between expected futures returns and a pricing kernel that is implied by a consumption-based asset pricing model. In this context, the pricing kernel is measured by the intertemporal marginal rate of substitution (IMRS) of a representative investor that is a function of only the growth rate in aggregate per capita consumption. If Equation (1.1) holds unconditionally, then unconditional expected returns are linear in one factor only (i.e. a standard unconditional Consumption CAPM prevails), and if Equation (1.1) holds conditionally, then for the unconditional expected returns a two factor unconditional model is obtained. Not only securities with higher consumption risk have higher unconditional expected returns (CCAPM), but also securities that have consumption betas that vary more with the market risk premium.

This standard consumption-based framework appears to be the most preferable, at least from a theoretical point of view. First, because it accounts for the intertemporal nature of the portfolio decision (Merton (1973), Breeden (1979)). Second, because it implicitly incorporates many forms of investors' wealth (not only stock market wealth) that are relevant for measuring systematic risk of assets (Mankiw and Shapiro (1986), Cochrane (2001)). Despite the theoretical appeal of the consumption-based model, empirical studies have not been successful in applying it to the cross-section of stock returns (Campbell and Cochrane (2000)). This problem has been addressed by a recent stream of literature, which focuses on the underlying assumption that investors can costlessly adjust their consumption (Jagannathan and Wang (2005), Parker and Julliard (2005)). We follow up on this research by applying it to a broader set of assets than stocks only. We use futures contracts that have as the underlying assets various commodities (agriculturals, meats, energy and precious metals) as well as currencies and an equity index. We study whether excess returns on futures contracts vary in a systematic way due to differences in consumption risk similarly to the returns on stocks. Historically, commodity futures have earned excess returns similar to those of equities (Gorton and Rouwenhorst (2006)), nevertheless they fulfill a different economic function. Moreover, since the underlying commodities are strongly related to aggregate consumption itself and may be used for hedging consumption risk, these futures markets seem to be a natural choice for testing consumption-based model. Finally, Lewellen, Nagel, and Shanken (2006) show that the tests of the asset pricing models based on the Fama-French size and book-to-market portfolios are often misleading, as these portfolios are known to have a strong factor structure, i.e. high time-series and cross-sectional predictability based on the Fama-French factors. Hence the use of futures returns, representing a separate asset class, only strengthens our tests.

We find that the Consumption CAPM explains up to 60 percent of the cross-sectional variation in mean futures returns. The conditional version of the consumption model performs best at the quarterly horizon and outperforms both the CAPM and the Fama-French three-factor model. We show that expected futures returns can be measured by the futures' yields and that the consumption model, next to explaining mean returns, is also best at explaining the cross-sectional variation in mean yields. Unlike for stock returns, ultimate consumption (i.e., contemporaneous plus future consumption) leads to lower performance of the consumption model. We show that demand and supply changes lead short term consumption risk to be important for commodities, but not long term consumption risk. We find that consumption betas measured with respect to the ultimate consumption growth fade out to zero and the consumption model controlling for the changes in production better explains the cross-section of futures returns. This suggests that for commodities we observe an impact of supply on commodity prices and therefore on consumption inducing time-varying consumption betas, whereas for stock markets the link between the supply (of stocks) and consumption is not to be expected. Thus, to the extent that commodity price changes are followed by changes in demand and supply, this may explain why ultimate consumption risk is not as good a risk measure for commodities as for stocks.

The second essay: *An Anatomy of Commodity Futures Returns: Time-varying Risk Premiums and Covariances,* assumes that Equation (1.1) holds conditionally and focuses on the time-series behavior of expected commodity futures returns. First, we decompose expected futures returns in the spot and term premiums. This decomposition is important, because the two risk premiums are likely to compensate for different risk factors (e.g. for oil futures the spot premium reflects the oil price risk, while the term premium mainly reflects the risk that is present in the convenience yields). We show that although average returns in commodity futures markets are claimed to be zero, the spot and term premiums that define them have opposite signs and both premiums are highly predictable. We are able to predict up to 30 percent of the time-variation in these risk premiums, with the spot premium being more predictable than the term premiums. This knowledge allows investors to design trading strategies that exploit these different premiums and their predictable variation.

The documented time-variation in expected futures returns or risk premiums is analyzed and confronted with three asset pricing models: the CAPM, the Fama-French three-factor model and the Consumption CAPM. We find that this predictability seems to be consistent with the consumption-based model but not with the CAPM or the Fama-French model. In other words, predictability documented in futures markets is consistent with the exposure to consumption risk that an investor is undertaking while following a trading strategy that exploits predictability, but not to the market risk or risks related to the Fama-French three factors. Since in the consumption-based model the risk of an asset is determined by its covariance with consumption growth, the time-varying expected returns should result from the time-varying conditional covariances between futures returns and consumption growth as follows from Equation (1.2). Indeed, we find that these covariances vary considerably over time. Consistent with the Breeden (1980) argument that the consumption betas of commodities may depend on their supply and demand elasticities, we find production growth to have stronger forecasting power for the conditional covariances than for futures returns.

The third essay: *Predictability in Industry Returns: Frictions Matter*, focuses in more detail on the predictability of asset returns and its relation to the asset pricing models. Following the work of Kirby (1998) we show that Equation (1.1) imposes restrictions on the slope coefficients and R^2s in predictive regression. In other words, predictability observed in the market must be consistent with the exposure to systematic risk that a rational investor is undertaking while following a trading strategy that exploits predictability, i.e. the profits from that trading strategy must be equal to a risk premium implied by the asset pricing model. It is well recognized that the ability to predict returns can exist in efficient markets, but what yet remains a puzzle is whether this predictability is rational. Kirby (1998) finds that in frictionless markets asset pricing models are not able to generate levels of predictability observed in the market. It may very well be the case though, that the profits documented in the literature are not attainable for the investor because of the market frictions present in the real world. The inability to go short or the presence of transaction costs may force investors to deviate from the trading strategy that aims to exploit predictability in the market, which may alter their profits. Hence, it is important to incorporate these deviations when assessing the rationality of trading strategies that track predictability.

The aim of this essay is to investigate the impact of the market frictions on the tests of the consistency of asset pricing theory with observed return predictability. We show how the restrictions derived by Kirby (1998) change when we take into account market frictions, such as short sales constraints and transaction costs. Incorporating short sales constraints weakens these restrictions. When the actual effect of some instruments is weaker in the market than suggested by the model, rational investors are willing to short sell these assets. However, being prohibited from doing so, investors might not be able to equate their profits with rational risk premiums. Thus, the asset pricing model with shorts sales constraints is only rejected when investors are over-compensated for true risk exposure. When we take into account transaction costs the restrictions are again weaker than in the frictionless markets, i.e. the higher the transaction costs, the weaker the restrictions. Moreover, in this case we are able to test to which extent transaction costs can reconcile predictability in financial markets, by deriving a threshold value for the transaction costs for which the coefficients from predictive regressions satisfy these weaker restrictions.

Futures markets can be assumed to be almost frictionless, which however, would be a very strong assumption for many other financial markets. Hence, we assess the impact of market frictions on the time-series behavior of asset returns by studying industry portfolios created from stocks traded in the major U.S. markets. We find strong evidence of return predictability among these industry portfolios, i.e., we can explain between 15 and 20 percent of return variance. Moreover, investors can enhance their investment opportunity set by adding active industry returns to the initial set of passive industry returns only, as they offer higher Sharpe ratios and higher risk-adjusted returns (relative to the factor models).

The results suggest that not taking into account market frictions may lead to incorrect conclusions. In frictionless markets, the documented predictability of industry returns does not seem to be consistent with rational asset pricing models, meaning that investors may be able to profit from the observed predictability more than what they expect to earn based on their exposure to risk. However, we find that these profits are only attainable if investors are able to trade without any costs. Transaction costs below 50 basis points are sufficient to reconcile much of the documented predictability. Furthermore, we find that a mean-variance investor significantly overstates his utility gain from return predictability that is not consistent with asset pricing models. When we incorporate market frictions these gains are substantially reduced.

Finally, in the last essay of this thesis: *Behavioral Factors in the Pricing of Financial Products*, we relax the assumption of rational asset pricing. In rational models agents are assumed to maximize their expected utility using identical probability beliefs for future states of the economy. We allow for behavioral biases on the side of the investor that may violate these assumptions and hence Equation (1.1).

In the last chapter we allow for these biases to explain mispricing that is observed in a particular class of securities, reverse convertible bonds. These are bonds that carry high coupon payments and in exchange, the issuer has an option at the maturity date to either redeem the bonds in cash, or to deliver a pre-specified number of shares. These bonds are mainly bought by individual investors who are not aware of the options, usually keep bonds in their portfolio and do not trade on the stock exchange, hence may be more prone to behavioral biases (i.e. may deviate from the behavior as suggested by rational asset pricing theory). We find that, on average, the plain vanilla RCs are overpriced by approximately 6%, while the knock-in RCs seem to be priced fairly. The documented overpricing seems to be driven by the option component. It is confirmed in a model-free analysis and is persistent for approximately one fourth of the lifetime of the reverse convertibles. Moreover, the documented overpricing remains significant in each year within our sample period. Given that the number of issuances increased over the sample period, this shows considerable economic losses to the investors in this market. Using a financial experiment in which we ask the participants to price a simple financial product with similar characteristics as a reverse convertible bond, we are able to test the role of behavioral factors like framing and cognitive errors, in explaining the documented overpricing. By showing that these factors are important we shed some light on the conclusion that the rational factors alone are not sufficient to explain the overpricing. Such an approach overcomes the difficulty (or even impossibility) in enumerating all possible rational explanations. We find that framing and cognitive errors, play an important role in the pricing of the simple financial product. Although the simple financial product is not exactly similar to a reverse convertible, our results shed some light on the ability of framing the redemption and the past stock price behavior to affect the pricing of the reverse convertible bonds.

Chapter 2

Consumption Risk and Expected Futures Returns

2.1 Introduction

Futures returns are like excess returns on assets such as stocks and bonds, whose expectations basically reflect risk premia. Understanding these risk premia is important for academics studying asset pricing models as well as for practitioners, since they are important input variables for portfolio and risk management models e.g. The determinants of futures risk premia are usually related to systematic risk based on the CAPM[1] or the Consumption CAPM (CCAPM) as in Jagannathan (1985). Although Jagannathan (1985) finds for three different agricultural futures contracts that the CCAPM implies significant risk premia and finds market prices of risk that are similar to those found in equity markets, he rejects the model itself. Breeden (1980) studies a similar model on a broader class of commodity futures and finds significant consumption betas but he does not perform a full test of the asset pricing model. The evidence proclaimed so far in the empirical literature, indicates that although commodity returns appear not to be related to the movements in stock market returns,[2] they do seem to be related to the changes in aggregate real consumption. The latter finding may be natural since part of the underlying commodities are strongly related to aggregate consumption itself and

[1] See, e.g., Dusak (1973), Black (1976), Carter, Rausser, and Schmitz (1983), Bessembinder (1992), and de Roon, Nijman, and Veld (2000).

[2] This is based on the unconditional version of the CAPM. However, futures contracts do exhibit systematic risk once betas are allowed to vary (e.g., Carter, Rausser, and Schmitz (1983)) and when, additionally, SMB and HML factors are included (e.g., Erb and Harvey (2006)).

may be used for hedging consumption risk. Hence, the consumption-based framework seems to be a natural choice for analyzing futures returns.

Previous studies find that the CCAPM has more difficulties in explaining the cross-section of stock returns than other models like the Fama-French three factor model (see Campbell and Cochrane (2000) and references therein).[3] This problem has been addressed by a recent stream of literature which focuses on the underlying assumption that investors can costlessly adjust their consumption plans. For instance, Jagannathan and Wang (2005) propose that consumption and investment decisions are made infrequently and show that the CCAPM explains more than 70 percent of the cross-sectional variation in expected stock returns when consumption growth is measured from the 4th quarter of one year to the next. Also, they find that lowering the frequency of consumption growth and returns from monthly to quarterly and annual data, significantly improves the performance of the CCAPM, which is likely to result from the smaller measurement error in consumption growth at lower frequencies. Parker and Julliard (2005) conjecture that consumption may be slow to respond to stock returns, and find that ultimate consumption risk, defined as the covariance of a stock return and consumption growth over the quarter of the return and many following quarters, explains between 44 and 73 percent of the cross-sectional variation in stock returns.

This chapter follows up on the aforementioned advances in the literature on the CCAPM by applying them to a broad cross-section of 25 different futures contracts. We study whether excess returns on futures contracts vary in a systematic way due to differences in consumption risk similarly to the returns on stocks. Historically, commodity futures have earned excess returns similar to those of equities (Gorton and Rouwenhorst (2006)). Nevertheless, they fulfill a different economic function than corporate securities such as stocks, i.e. they do not represent claims against future cash flows of the firm, but bets on the future expected spot prices of commodities. They also constitute a broader class of assets than simply stock returns, since they have as the underlying assets various commodities (agriculturals, meats, energy and precious metals), as well as currencies, bond and equity indices. The CCAPM may be particularly relevant to commodity futures as commodities are closely linked to consumption and production factors.

[3] A second difficulty for the CCAPM is that it cannot explain the time-series average of stock returns, i.e., the high equity premium. In response to this, several refinements of the model have been put forward. These models focus on better ways of modeling investors preferences. For example, the model of Bansal and Yaron (2004) which uses the recursive utility preference of Epstein and Zin (1989, 1991) , or the Campbell and Cochrane (1999) model which allows for a habit formation in the utility specification; appear to be successful in solving these puzzles.

Moreover, there are important differences between the consumption betas in stocks and in futures markets. First, for (commodity) futures it is common to observe positive as well as negative consumption betas, a feature less common in equity markets. Second, the contemporaneous consumption beta for longer maturity futures is usually lower than for shorter maturity futures (Breeden (1980)), which suggests that the time period over which consumption risk is measured may play an important role in determining the consumption risk in futures markets, unlike in stock markets. Finally, Lewellen, Nagel, and Shanken (2006) show that tests of the asset pricing models based on the Fama-French size and book-to-market portfolios are often misleading, as these portfolios are known to have a strong factor structure, i.e. high time-series and cross-sectional predictability based on the Fama-French factors. Hence the use of futures returns, representing a separate asset class, only strengthens our tests.

We find that, at the quarterly horizon, the (unconditional) CCAPM explains about 50 percent of the cross-sectional variation in mean futures returns, while there is almost no explained variance at the monthly level, and an intermediate result at the yearly level. This pattern is consistent with the results found by Jagannathan and Wang (2005) based on stock portfolios. However we find somewhat lower implied consumption risk premiums for our futures contracts. When we assume that the model holds in a conditional sense (as in Jagannathan and Wang (1996)), allowing for time-varying betas and risk premiums, the CCAPM explains up to 60 percent of the cross-sectional variation in futures returns and again shows the best performance at the quarterly and annual frequency. In both cases, the consumption-based model explains the futures returns better than our benchmark models: the CAPM or the Fama-French model. As in previous empirical studies the CCAPM does show a high implied risk aversion though.

Using ultimate consumption risk as in Parker and Julliard (2005), we find that the performance of the CCAPM is best using consumption growth of the contemporaneous quarter of the returns, but then deteriorates for the longer horizons. Although this contradicts the findings of Parker and Julliard (2005) for stock returns, it is consistent with the finding that the CCAPM performs best at the quarterly frequency and may be the result of supply and demand elasticities of many of the commodities that underlie our futures contracts, inducing time-varying consumption betas. Indeed, we find that there are systematic decreases in the absolute values of the consumption betas of our commodities as the horizon, over which consumption growth is measured, increases. Consistent with the conjecture that production adjusts to changes in commodity prices but only slowly, we find that the variation in commodity returns explained by the investment growth model first increases with the measurement horizon, and then decreases. A similar pattern is observed when we estimate the consumption model controlling for changes in production. This suggests that for commodities we observe an impact of supply on commodity prices and therefore on consumption inducing time-varying consumption betas, whereas for stock markets the link between the supply (of stocks) and consumption is not to be expected. Thus, to the extent that commodity price changes are followed by changes in demand and supply, our results may explain why ultimate consumption risk is not as good a risk measure for commodities as for stocks.

Finally, using a simple present value relation, we show that the futures' own yield can be used as an estimator of expected returns similar to the way dividend yields are estimators of expected stock returns (see, e.g., Campbell and Shiller (1988) and Bekaert and Harvey (2000)). The futures' yield has the advantage over the simple mean return that it is an ex ante measure of expected returns, while the mean return is an ex post measure. Using the average yield as the dependent variable in the cross-sectional regression, confirms that the CCAPM performs best at the quarterly frequency. However, the model can explain only up to 29 percent of the cross-sectional variation in yields in the unconditional case and up to 36 percent in the conditional case. The Fama-French model explains the cross-sectional variation in yields better (up to 45 and 58 percent respectively), but yields negative estimates of the market risk premia.

The rest of this chapter is structured as follows. The next section gives a brief outline of the unconditional and the conditional CCAPM. Section 2.3 discusses some estimation issues and Section 2.4 describes the data. The empirical results are discussed in Section 2.5 and Section 2.6 concludes.

2.2 Theory: Expected futures returns and consumption risk

2.2.1 Consumption-based models for expected returns

According to finance theory, expected returns on securities are determined by their exposure to systematic economy wide risk. Rubinstein (1976) and Breeden (1979) show that the risk of a security is determined by its covariance with consumption growth (CCAPM). In this framework, a representative agent allocates her resources among consumption and different investment opportunities in order to maximize her utility over lifetime consumption:

$$E\left[\left(\sum_{s=t}^{\infty}\delta^{s}u\left(C_{s}\right)\right)\mid F_{t}\right], \tag{2.1}$$

where we assume a time and state separable Von Neumann-Morgenstern utility function $u(\cdot)$, C_s denotes consumption expenditures in period s, δ is the time discount factor, and F_t denotes the information set available to the representative agent at time t. The first order conditions of the agent's maximization problem subject to the standard budget constraints imply the following relation that is satisfied by all financial securities:

$$E_t\left[\left(\delta^{j}\frac{u'\left(C_{t+j}\right)}{u'\left(C_{t}\right)}\right)r_{i,t+j}\right]=0 \tag{2.2}$$

where $r_{i,t+j}$ is the excess return on any security i, from date t to $t+j$, $u'(\cdot)$ denotes first derivative of the period utility function, and $E_t[\cdot]$ denotes the expectation conditioned on the information available at time t.

2.2.2 The unconditional Consumption CAPM

In the empirical analysis we work with both the unconditional and conditional versions of (2.2). We start with the unconditional model. Defining the stochastic discount factor (SDF) as

$$m_{t+j}\equiv\delta^{j}\frac{u'\left(C_{t+j}\right)}{u'\left(C_{t}\right)}$$

gives:

$$\begin{aligned} E\left[m_{t+j}r_{i,t+j}\right] &= 0 \\ &\Longleftrightarrow\quad E\left[r_{i,t+j}\right]=-\frac{Cov\left[r_{i,t+j},m_{t+j}\right]}{E\left[m_{t+j}\right]} \end{aligned}$$

where the second equality follows from using the definition of covariance and by applying the law of iterated expectations. Defining the sensitivity of excess returns $r_{i,t+j}$ to changes in the stochastic discount factor as $\beta_{ic,j}=\frac{Cov[r_{i,t+j},m_{t+j}]}{Var[m_{t+j}]}$ and the market price of risk $\lambda_c=-\frac{Var[m_{t+j}]}{E[m_{t+j}]}$ we get

$$E\left[r_{i,t+j}\right]=\lambda_c\beta_{ic,j}. \tag{2.3}$$

This is the standard beta representation of the unconditional Consumption CAPM. Expected excess returns on different securities are determined by their covariances with the stochastic discount factor, and thus by their covariances with consumption. A security with greater consumption risk has a higher expected return, since consumption and marginal utility are inversely related. Later on we also consider other specifications for the stochastic discount factor implied by the CAPM (i.e. the SDF linear in the market return only) and by the Fama-French three factor model (i.e. the SDF linear in three risk factors: market, size and book-to-market).

2.2.3 The conditional Consumption CAPM

To model the implications of the conditional version of Equation (2.2):

$$E_t\left[r_{i,t+j}\right] = \lambda_{0c,t} + \lambda_{1c,t}\beta_{ic,t}, \tag{2.4}$$

for the unconditional expected returns, we follow Jagannathan and Wang (1996). First, take unconditional expectations of (2.4):

$$E\left[r_{i,t+j}\right] = \lambda_{0c} + \lambda_{1c}\overline{\beta}_{ic} + Cov\left[\lambda_{1c,t}, \beta_{ic,t}\right] \tag{2.5}$$

where $\overline{\beta}_{ic} = E\left[\beta_{ic,t}\right]$ and $\lambda_{1c} = E\left[\lambda_{1c,t}\right]$. Then, projecting $\beta_{ic,t}$ on the conditional market risk premium $\lambda_{1c,t}$, gives:

$$\beta_{ic,t} = \overline{\beta}_{ic} + \varphi_{ic}\left(\lambda_{1c,t} - \lambda_{1c}\right) + \eta_{ic,t} \tag{2.6}$$

with $E\left[\eta_{ic,t}\right] = E\left[\eta_{ic,t}\lambda_{1c,t}\right] = 0$. Finally, substituting (2.6) into (2.5) gives for the unconditional expected returns:

$$\begin{aligned} E\left[r_{i,t+j}\right] &= \lambda_{0c} + \lambda_{1c}\overline{\beta}_{ic} + Var\left[\lambda_{1c,t}\right]\varphi_{ic}, \\ \varphi_{ic} &= \frac{Cov\left[\lambda_{1c,t}, \beta_{ic,t}\right]}{Var\left[\lambda_{1c,t}\right]}. \end{aligned} \tag{2.7}$$

Thus, the conditional CCAPM leads to a two-factor unconditional model, in which the second factor is a risk premium induced by the covariance between the conditional beta $\beta_{ic,t}$ and the conditional market risk premium for consumption risk $\lambda_{1c,t}$. Not only securities with higher expected betas have higher unconditional expected returns, but also securities with betas that vary more with the risk premium have higher unconditional expected returns, i.e. a positive covariance implies that if $\beta_{ic,t}$ is high when $\lambda_{1c,t}$ is high, which will result in higher unconditional expected returns.

The conditional model expressed in this way requires estimation of the expected beta, $\overline{\beta}_{ic}$ and the sensitivity of the conditional beta to the risk premium, φ_{ic}, which cannot be done directly. Alternatively, we can directly estimate the average reaction of the returns to the changes of the stochastic discount factor and the average reaction to the changes of the risk premium. This leads to the following unconditional betas:

$$\begin{aligned} \beta_{ic} &\equiv \frac{Cov\left[r_{i,t+j}, m_{t+j}\right]}{Var\left[m_{t+j}\right]}, \\ \beta_{i\varphi} &\equiv \frac{Cov\left[r_{i,t+j}, \lambda_{1c,t}\right]}{Var\left[\lambda_{1c,t}\right]}. \end{aligned} \tag{2.8}$$

Jagannathan and Wang (1996) show that if $\beta_{i\varphi}$ is not a linear function of β_{ic}, then there exist some constants a_0, a_1, a_2 such that for every security i the unconditional expected return is a linear function of the above two unconditional betas:

$$E\left[r_{i,t+j}\right] = a_0 + a_1\beta_{ic} + a_2\beta_{i\varphi}. \tag{2.9}$$

We only summarize the idea of the proof here, for details see Appendix 2.A or the proof of Theorem 1 in Jagannathan and Wang (1996). First it is shown that when betas vary over time, then $(\beta_{ic}, \beta_{i\varphi})$ is a linear function of $(\overline{\beta}_{ic}, \varphi_{ic})$, which follows from additional assumptions about the residual term from projection equation $\eta_{ic,t}$. Second, when $\beta_{i\varphi}$ is not linear in β_{ic} (i.e. when the single beta CCAPM does not hold unconditionally, even though it holds conditionally), then $(\beta_{ic}, \beta_{i\varphi})$ will contain all necessary information contained in $(\overline{\beta}_{ic}, \varphi_{ic})$. Hence, expected returns will be linear in $(\overline{\beta}_{ic}, \varphi_{ic})$ as well as in $(\beta_{ic}, \beta_{i\varphi})$.

2.2.4 Ultimate Consumption Risk

Recently, Parker and Julliard (2005) find that contemporaneous consumption risk, as in the models discussed in the previous sections, is not sufficient to explain the cross-section of stock returns. They propose to extend the contemporaneous measure with the subsequent time periods to account for possible slow consumption adjustment. To see this, let us rearrange the terms in (2.2) in the following way:

$$E_t\left[u'\left(C_{t+j}\right) r_{i,t+j}\right] = 0.$$

Combining the above with the Euler equation for the risk-free rate between time $t+j$ and $t+j+S$:

$$E_{t+j}\left[\delta u'\left(C_{t+j+S}\right) R^f_{t+j,t+j+S}\right] = u'\left(C_{t+j}\right),$$

gives the following representation for expected returns:

$$\begin{aligned} E\left[r_{i,t+j}\right] &= \lambda_{c,S}\beta_{ic,S}, \\ \beta_{ic,S} &= \frac{Cov\left[r_{i,t+j}, m_{t+j}^{S}\right]}{Var\left[m_{t+j}^{S}\right]}, \\ m_{t+j}^{S} &= \delta R_{t+j,t+j+S}^{f}\frac{u'\left(C_{t+j+S}\right)}{u'\left(C_{t}\right)}, \end{aligned} \tag{2.10}$$

where $Cov\left[m_{t+j}^{S}, r_{i,t+j}\right]$ for large S is referred to as ultimate consumption risk and the market price of this risk is $\lambda_{c,S} = -\frac{Var\left[m_{t+j}^{S}\right]}{E\left[m_{t+j}^{S}\right]}$.

We apply this approach to measure consumption risk in futures contracts. However, there are important differences between the consumption betas in stocks and in futures markets. First, for futures it is common to observe positive as well as negative consumption betas, a feature less common in equity markets. Second, as Breeden (1980) shows, the contemporaneous consumption beta for longer maturity futures is usually lower than for shorter maturity futures, due to supply responses. He argues that for short time-to-maturity futures, supply and demand elasticities may be assumed to be relatively small. As the time-to-maturity increases supply responses start to affect consumption-betas. This suggests that the time over which the consumption risk is measured will play an important role in determining the consumption risk in futures markets.

2.3 Estimation issues

This section presents the estimation issues. We, first, discuss the estimation of the stochastic discount factor and the sensitivity of futures returns to changes in this stochastic discount factor. Second, we discuss the estimation of the expected futures returns.

2.3.1 Estimating the CCAPM

We use the two stage cross-sectional regressions (CSR) approach with standard errors corrected for the estimation error in the dependent variable and for the fact that $\beta' s$ are pre-estimated as suggested by Fama and MacBeth (1973), Shanken (1992), and Jagannathan and Wang (1996). Moreover, since our sample consists of return histories that differ in length, we apply the procedure of Stambaugh (1997) to compute the multivariate moments without discarding any observations. The validity of the models is examined by testing whether Jensen's alphas are zero (see Appendix 2.B for details).

To parameterize the consumption-based model we assume that the period utility function has a constant relative risk aversion γ. This implies the following for the stochastic discount factor:

$$m_{t+j} = \delta^j \left(\frac{c_{t+j}}{c_t}\right)^{-\gamma},$$

where $\left(\frac{C_{t+j}}{C_t}\right)^{-\gamma}$ is the period-j growth in per capita consumption from time t to time $t+j$. Given the above representation of the SDF, expected returns are a non-linear function of consumption growth. In the following, we assume that consumption growth and security returns are jointly log-normally distributed, which implies that the expected excess returns are linear in log-consumption growth:

$$E\left[r_{i,t+j}\right] + 0.5Var\left[r_{i,t+j}\right] = \gamma Cov\left[r_{i,t+j}, \Delta c_{t+j}\right], \tag{2.11}$$

where $\Delta c_{t+j} \equiv \log\left(\frac{C_{t+j}}{C_t}\right)$. The above can be also expressed in the following beta representation:

$$\begin{aligned} E\left[r_{i,t+j}\right] &= \lambda_0 + \lambda_c \beta_{ic,j}, \\ \beta_{ic,j} &= \frac{Cov\left[r_{i,t+j}, \Delta c_{t+j}\right]}{Var\left[\Delta c_{t+j}\right]}. \end{aligned} \tag{2.12}$$

where the implied coefficient of relative risk aversion is $\gamma = \frac{\lambda_c}{Var[\Delta c_{t+j}]}$ and the intercept is $\lambda_0 = -0.5Var\left[r_{i,t+j}\right]$. A similar beta representation can be obtained, without the need to assume log normality but by using a Taylor series approximation of the stochastic discount factor around expected consumption growth.

In order to account for possibly slow consumption adjustment the log-consumption growth is measured over an extended horizon:

$$\Delta c^S_{t+j} = \log\left(\frac{C_{t+j+S}}{C_t}\right). \tag{2.13}$$

See Appendix 2.C for details on the derivations. In addition, the conditional model requires observations on the conditional market risk premium $\lambda_{1c,t}$. We follow the approach of Jagannathan and Wang (1996) utilizing the fact that a variable that helps predict the business cycle can also forecast the market risk premium. The logic behind this is based on the presumption that if prices vary over the business cycle, so might the market risk premiums. The empirical research on predictability has identified several potential variables, from which the most widely used are: a dummy for the January effect; a credit risk premium defined as the difference in yields between Moody's Baa rank bonds and Moody's Aaa rank bonds; a term structure premium defined as the difference between

90 days and 30 days Treasury Bill rate; a dividend yield on the S&P 500 index; and the return on the market index (see, e.g., Kirby (1998), Pesaran and Timmermann (1995), and Ferson and Harvey (1991)). Based on previous studies we use a term structure variable $\left(r_{t+1}^{term}\right)$.[4] Assuming that the market risk premium is linear in the conditioning variable, i.e. $\lambda_{1c,t} = b_0 + b_1 r_{t+1}^{term}$, we can estimate the following conditional model:

$$\begin{aligned} E\left[r_{i,t+j}\right] &= \lambda_0 + \lambda_1 \beta_{ic} + \lambda_{term} \beta_{i,term} \\ \beta_{ic} &\equiv \frac{Cov\left[r_{i,t+j}, \Delta c_{t+j}\right]}{Var\left[\Delta c_{t+j}\right]}, \\ \beta_{i,term} &\equiv \frac{Cov\left[r_{i,t+j}, r_{t+j}^{term}\right]}{Var\left[r_{t+j}^{term}\right]}. \end{aligned} \tag{2.14}$$

2.3.2 Yield-based measure for expected returns

Traditionally, expected returns are measured as the averages of past returns. However, the estimates of means are sensitive to the number of observations and volatility of the return series (Merton (1980)). In this section we show that a present value model implies the use of yields as an alternative measure of expected returns. The futures' yield has the advantage over the mean return that it is an ex ante measure of expected returns, while the mean return is an ex post measure.

To see the relation between commodity prices and yields we start from a simple present value model.[5] Define P_t to be the spot price of a commodity, and D_t to be a benefit from having the commodity available, i.e. the convenience yield net of storage and insurance costs. Later in the empirical section next to commodity futures we also use financial futures. For index futures P_t is the index, and D_t are dividends (analogously to common stocks); for foreign currency futures P_t is the spot price of the currency, and D_t are the interests payments from a foreign deposit. Then, the net return on a commodity from period t to period $t+1$ is:[6]

$$R_{t+1} = \frac{P_{t+1} - P_t + D_t}{P_t}. \tag{2.15}$$

Assuming that the expected returns are constant, i.e. $E_t\left[R_{t+1}\right] = \mu$ and D_t is expected to grow at a constant rate g gives a standard Gordon-growth model for a commodity

[4] We also experimented with other predictive instruments, but our results are robust with respect to the choice of the instrument.

[5] A similar approach is used by Pindyck (1993).

[6] Notice that the definition of a commodity return that is used here differs from commonly used commodity returns, $R_{p,t+1} = P_{t+1}/P_t - 1$, which consist of price changes only. Similar to total stock returns our definition includes the cash yield D_t.

spot price:[7]

$$P_t = \frac{D_t}{\mu - g},$$

where $\mu > g$. This relation implies that we can measure expected returns on commodities as the sum of the cash yields and growth rate in convenience yields:

$$\mu = \frac{D_t}{P_t} + g. \tag{2.16}$$

Dynamic versions of this approach are used by Bekaert and Harvey (2000) e.g. For many commodities, the growth rate g is - at least in the long run - close to zero, at least in real terms. If the growth rate for commodities is indeed close to zero, then it follows immediately from (2.16) that the cash yield measures the expected total return on commodities. We test this presumption below. Thus, next to the standard way of estimating expected returns using historical averages we have an alternative measure based on yields.

A natural way to estimate yields is to use the information that is present in futures prices. Define $F_t^{(n)}$ to be the commodity futures price for delivery at time $t+n$. Assuming that the cost-of-carry model holds, we have:

$$\begin{aligned} F_t^{(n)} &= P_t \exp\{-y_t^{(n)} \times n\}, \\ f_t^{(n)} &= p_t - n \times y_t^{(n)}, \end{aligned} \tag{2.17}$$

where $p_t = \log(P_t)$, $f_t = \log(F_t)$ and $y_t^{(n)}$ is the per-period yield for maturity n. By a no arbitrage argument, this yield is equal to the net cash yield (i.e. the cash flow D_t expressed as the percentage of price: $s_t = d_t - p_t$) minus the n-period interest rate:

$$y_t^{(n)} = s_t^{(n)} - i_t^{(n)}. \tag{2.18}$$

In general, this net cash yield, $s_t^{(n)}$, consists of the benefits that the owner of the security receives from holding the security from time t to time $t+1$ minus the costs of holding (storing) the security during the same period. For commodity futures the convenience yield constitutes the benefits from having a commodity available, while the cost of carrying the commodity to the future involves interest costs, physical storage costs, and insurance premiums. For financial futures there are no storage costs and the benefits from keeping the underlying asset are for instance the foreign interest rate for currency futures and the dividend yield for stock index futures.

[7] Additionally, we need to assume that the expected discounted value of the stock price K periods from the present shrinks to zero as the horizon K increases, which will be satisfied unless the stock price is expected to grow forever.

Then, a one-period log futures return, $r^{(1)}_{f,t+1}$, can be decomposed in the following way:

$$\begin{aligned} r^{(1)}_{f,t+1} &= p_{t+1} - f^{(1)}_t = p_{t+1} - p_t + y^{(1)}_t \\ &= p_{t+1} - p_t + s^{(1)}_t - i^{(1)}_t = r_{t+1} - i^{(1)}_t \end{aligned} \tag{2.19}$$

Thus, the one-period futures return, $r^{(1)}_{f,t+1}$, is like an excess return on the total commodity return, r_{t+1}. Therefore, adding the one-period interest rate $i^{(1)}_t$ to (2.19), taking the expectations of both sides, and using the log version of (2.16) we get:

$$E\left[r^{(1)}_{f,i,t+1} + i^{(1)}_t\right] = s_t + g, \tag{2.20}$$

with $s_t = d_t - p_t$. Thus, using the assumption that the growth rate g is zero, we can relate futures returns to yields in the following way:

$$r^{(1)}_{f,i,t+1} + i^{(1)}_t = a_i + b_i s^{(1)}_{i,t} + e_{i,t+1}. \tag{2.21}$$

Subtracting the one-period interest rate $i^{(1)}_t$ from both sides gives

$$r^{(1)}_{f,i,t+1} = \alpha_i + \beta_i y^{(1)}_{i,t} + \varepsilon_{i,t+1}. \tag{2.22}$$

At each point in time the expected one-period futures return is proportional to the per-period yield for the same one-period. Equation (2.22) shows that it is very natural to relate futures returns to yields if the growth rate in convenience yields is indeed zero.

Table 2.1 tests the presumption of zero growth rates in convenience yields for our dataset of 25 futures contracts (described in detail in Section 2.4). From (2.17) the per-period yields (y^n_t) are computed as the log price differences between the nearest-to-maturity contracts and the ones that are closest to having a maturity 12 months longer than the nearest-to-maturity contracts correcting for the varying length of spread. Then, from (2.18) the convenience yields are computed by correcting the yields with the interest rate over the same maturity. Finally, the table reports the average growth rates in convenience yields, their standard errors and the t-statistics for testing the significance of means. The results suggest that these growth rates are insignificantly different from zero, although this conclusion should be interpreted with caution since the standard errors are rather high.

Given that the estimated growth rates are insignificant, we expect a strong relation between the two measures for expected returns: return- and yield-based measure. Figure 2.1 depicts the cross-sectional relation between the annualized average log returns on the nearest-to-maturity futures contracts, and the corresponding annual log yield. The plotted lines represent fitted values from the following cross-sectional regression of mean futures returns on mean yields:

$$\overline{r}_{f,i} = \alpha + \beta \overline{y}_i + u_i. \tag{2.23}$$

The solid line depicts results from a regression with an intercept and the starred line from the regression without an intercept. This figure shows a strong, positive relation between mean returns and yields. This is confirmed by the high estimated R^2 of the the above regression: 61.3% of the cross-sectional variation in mean returns is explained by the cross-sectional variation in mean yields. The results are reported in Table 2.2. The estimated intercept $\widehat{\alpha}$ is insignificantly different from zero and is equal to 2.6% per annum (with a standard error of 1.7%). When β in the cross-sectional regression is restricted to be one, then the intercept is equal to 2.5% pa with a standard error of 1.6%. This estimate of 2.5% can be interpreted as the average growth rate in yields over all 25 futures contracts (i.e., the average of the growth rates reported in Table 2.1), which confirms the presumption of zero growth rate in futures yields despite the high standard errors reported earlier. The estimated $\widehat{\beta}$ is in both cases (when we force an intercept to be zero and not) within two standard errors from one. When we do not impose restrictions on the intercept $\widehat{\beta}$ is equal to 1.09 (with a standard error of 0.38), and when we force an intercept to be zero, it decreases to 0.88 (with a standard error of 0.39).

2.4 Data

2.4.1 Futures data

We use data on 25 futures contracts that are obtained from the Futures Industry Institute (FII) Data Center. The starting date of our sample period varies between contracts, as we use all available information for each futures contract. The earliest starting date is February 1968. The end date, December 2004, is common for all series. Hence the number of observations varies between futures contracts in our sample.

The data can be divided into 20 commodity futures contracts and five financial futures contracts.[8] The commodities comprise grains (3), oil and meals (3), meats (4), energy (3), precious metals (4), and food and fiber (3). The financial contracts consist

[8] The classification we use is similar to the one used by the Institute for Financial Markets (IFM).

of an equity index (1) and foreign currencies (4). These markets have relatively large trading volumes and provide a broad cross-section of futures contracts. Details about the delivery months, the exchanges where these futures contracts are traded and the starting dates for each contract are given in Table 2.3.

As outlined in Section 2.3.2, our dependent variable - the expected return - is measured in two ways: based on returns and yields. Futures returns are calculated using a rollover strategy of nearest-to-maturity futures contracts. Until the delivery month, we assume a position in the nearest-to-maturity contract. At the start of the delivery month, the position is changed to the contract with the following delivery month, which then becomes the nearest-to-maturity contract. Prices of futures observed in the delivery month are excluded from the analysis to avoid irregular price behavior that is common during the delivery month. Depending on the delivery dates during the year, the different series are for delivery one to three months apart. We obtain a minimum of 194 and a maximum of 442 observations.

The second measure of expected returns, derived from the present value model, is based on futures yields. To avoid the problems of seasonal fluctuations in futures (convenience) yields, yearly yields are used. We construct the series of annual yields as the log price difference between the nearest-to-maturity contracts and the ones that are closest to having a maturity 12 months longer than the nearest-to-maturity contracts. Depending on the series, the maturities vary between 7 to 13 months. To correct for the varying length of the spread, we use yields projected on the maturity equal to exactly 12 months.

Descriptive statistics are presented in Table 2.4. Panel A describes the returns on 25 futures markets. The first three columns give the annualized mean returns computed for different frequencies. Consistent with previous studies[9] we find that except for a few futures contracts (S&P 500, crude oil, unleaded gasoline and live cattle futures) the estimated mean returns are statistically indistinguishable from zero at the 5% significance level. The highest average returns - more than 10% on an annual basis - are earned by energy futures. For some futures, e.g., soybean oil, cotton, coffee, and copper, we observe large differences in mean returns across the different frequencies of the data. Finally, the last column gives the annualized yields for different futures. The table shows that the cross-section of mean yields is smoother than of mean returns. For instance, the dispersion between the minimum and the maximum yield is smaller than for the mean

[9] See. e.g., Bessembinder (1992), Bessembinder and Chan (1992), and de Roon, Nijman, and Veld (2000).

returns.[10]

2.4.2 Consumption data

It is a well known fact that reported consumption data are subject to measurement problems. Theory implies that consumption risk is measured with respect to aggregate consumption growth between two points in time. In practice, however, we observe total expenditures on goods and services over a period of time. This creates a so called "summation (or time-aggregation) bias" (e.g., Breeden, Gibbons, and Litzenberger (1989)).

One way to avoid this problem is to use higher frequency consumption data. On the other hand, high frequency consumption data are measured less precisely, which may lead to less reliable (less stable) estimates. The higher frequency data may exhibit seasonal patterns, which might be especially important among the returns on commodity futures.[11] Moreover, recent work by Jagannathan and Wang (2005) shows that consumption-risk measured with lower frequency data, can better explain the cross-section of the 25 Fama-French portfolios. Since establishing which of the aforementioned biases dominate in futures markets remains an empirical issue, we use monthly, quarterly and yearly consumption data in our empirical tests.

Following the literature, we measure consumption growth as the percentage change in the seasonally adjusted, aggregate, real per capita consumption expenditures on non-durable goods and services. We use monthly, quarterly and annual consumption and population data from the National Income and Product Accounts (NIPA) tables in Section 2 on Personal Income and Outlays. The sample period is dictated by the availability of futures prices, as the consumption data at all frequencies are observed at a longer time interval.

Panel B of Table 2.4 gives the descriptive statistics for the log consumption growth. The consumption growth during our sample period is slightly above 2% per annum

[10] We sometimes observe rather extreme returns, usually related to specific events. One example is the silver bubble in the turn of 1979. By the early 1970s silver began to rise in price, along with gold, platinum, oil, inflations and U.S. interest rates. The Commodities Futures Trading Commission falsely attributed the rise in silver prices to the market manipulations and changed the trading rules (i.e., margin requirements were raised to 100%, only futures sell orders were allowed), which lead to a collapse of the silver bubble. This is reflected in our data, where we observe almost 300% annual return for silver in 1979. In general we observe more volatility in the futures data, which is reflected in rather high standard deviations reported earlier. Since, these are inherent features of futures data we do not exclude any observations.

[11] For example, futures contracts on grains may exhibit seasonality around (due to) the harvest times.

for all frequencies. Monthly consumption exhibits the highest growth and the highest volatility.

Benchmark factors

For the benchmark models we use two standard models: the CAPM and the Fama-French three-factor model. Since futures contracts are in zero net supply they do not enter the market portfolio, hence the CAPM also holds in economies where not only stocks but also futures are traded (de Roon, Nijman, and Veld (2000)). It remains an empirical question though, whether the two additional factors (size and book-to-market) improve the cross-sectional predictability of futures returns (see, e.g., Erb and Harvey (2006)). The standard benchmark research factors are retrieved from Kenneth French's online data library. As these data are only available on a monthly and an annual basis, we compute quarterly returns by compounding monthly returns. Panel C of Table 2.4 gives the descriptive statistics for the benchmark factors, which confirms their standard features. In contrast to the mean futures returns given in Panel A, benchmark factors mean returns do not vary substantially across different frequencies.

2.5 Empirical analysis

2.5.1 Unconditional consumption risk

We start our empirical analysis with the unconditional version of the CCAPM in Equation (2.3). Table 2.5 provides the cross-sectional estimates of λ_0 and λ_c, based on our 25 futures contracts. Panel A reports the regression estimates for betas estimated at different frequencies: monthly, quarterly and yearly. Estimating beta at a monthly frequency leads to a very poor performance of the consumption model. The R^2 of the cross-sectional regression is 2.5%, and the market price of consumption risk is not significantly different from zero.

At lower frequencies, the CCAPM fares much better: for quarterly estimates, the R^2 increases to 51% and for yearly estimates it is 35%. As in Lewellen, Nagel, and Shanken (2006) the 95% confidence intervals for the true R^2 are rather wide though, which may result from the use of only 25 cross-sectional observations. Nevertheless, the lower bounds are always above zero for the unadjusted R^2s. A similar pattern shows up for the benchmark models: all models have the highest R^2 for quarterly estimates, and essentially zero R^2s for monthly estimates. However, for both quarterly and yearly estimates, the consumption model exhibits by far the best performance, while the R^2

for the benchmark models never exceeds 30%.

In evaluating whether the Jensen's alphas are zero, we test whether the estimated intercept is equal to half of the variance of futures returns (see Appendix 2.B for details). Again, the consumption-based model fairs better than the benchmark models as it generates insignificant Jensen's alphas for quarterly and yearly returns, while the CAPM and the Fama-French model yield alphas significantly different from zero at all frequencies. The implied consumption risk premium, λ_c, is about one percent per year based on quarterly estimates and 68 basis points based on yearly estimates. These estimates are somewhat lower than the estimates found by Jagannathan and Wang (2005) based on stock portfolios, but the order of magnitude and the patterns that we find are comparable, except for the fact that for our futures data quarterly estimates provide the best results while they find yearly returns to give the best fit of the CCAPM for stock returns.

The ability of the CCAPM to explain the cross section of futures returns well on the one hand, gives very high estimates for the risk aversion of the representative investor on the other hand. However, this result is consistent with other empirical studies on stock market returns (e.g., the evidence varies from risk aversion between 20 and 40 in Parker and Julliard (2005) and Jagannathan and Wang (2005) to 160 in Duffee (2005)). This result is also consistent with numerous theoretical explanations for the equity premium (e.g., heterogenous consumers in Constantinides and Duffie (1996), habit formation in Campbell and Cochrane (1999), or infrequent revision of consumption and investment decisions in Lynch (1996)), which makes the linear relation between expected returns and the covariance with consumption growth hold only approximately resulting in a high implied coefficient of risk aversion.

Panel B of Table 2.5 reports similar results, but here we use the average futures yields as a measure of expected return. The results in Panel B demonstrate again the best performance for quarterly estimates, but now the Fama-French three factor model exhibits the highest R^2 (44%), while the CAPM and the CCAPM show similar performances in terms of R^2 (26% and 28% respectively).[12] However, both the CAPM and the Fama-French model imply negative market risk premiums, λ_{mkt}, whereas the CCAPM consistently yields positive consumption risk premiums for the quarterly and yearly estimates. The consumption risk premiums λ_c are now only about half the premiums that

[12] Given the large numer of parameters needed to simulate the distribution of R^2 here (i.e. we would need to estimate the moments of the joint distribution of returns, yields and factors) we refrain from reporting the confidence intervals.

we found in Panel A. None of the models show a Jensen's alpha significantly different from zero.[13]

Figure 2.2 illustrates these findings graphically. This figure illustrates, that even though it is more difficult to explain the cross-section of yields (as follows from the R^2s), the pricing errors that result from using the yields as an expected return measure are much smaller than the pricing errors that follow from using the mean returns. This basically follows from the lower volatility in yields versus mean returns and is confirmed in the estimates of the absolute pricing errors. We measure pricing errors as the absolute value of the error term implied by the cross-sectional regression. When mean past returns are used the smallest pricing errors are implied by the consumption-based model (i.e., 3.0%, while both the CAPM and the FF models imply 4.1%). Moreover, for all models these pricing errors are above the ones implied by the yield-based expected returns. These latter errors are similar across all models (i.e., 2.6%, 2.9%, and 2.4% respectively), though the Fama-French three factor model yields the lowest errors. Figure 2.2 shows also that our results are not affected by the inclusion of financial futures. This is confirmed in auxiliary estimations (which are available from the authors on request). When we estimate all the models using only 20 commodity futures we find results very similar to the ones reported here. We opt for the use of the broader cross-section of 25 contracts to include more information on futures returns.

Thus, based on the R^2s and the sign of the risk premiums, the consumption CAPM explains the cross-section of expected futures returns best using quarterly estimates. The implied consumption risk premiums are somewhat lower than the estimates found in stock markets, but the order of magnitude and the patterns that we find are comparable.

2.5.2 Conditional consumption risk

Table 2.6 provides the estimates based on the conditional CCAPM in (2.14). Similar to Table 2.5, we report estimates based on average futures returns in Panel A and estimates based on yields as an expected return measure in Panel B.

Panel A indicates that for all frequencies the conditional models show a much better performance than the unconditional models in Table 2.5. It is only for the quarterly estimates of the consumption model that the R^2 is less than ten percentage points higher for the conditional model (59% versus 51%). In all other cases the R^2 improves

[13] We find that the results are not driven by the fact that the yield-based measure of expected returns does not include the growth rate in dividends on the S&P 500 index by testing the alphas without the S&P 500 futures.

by at least ten percentage points, and often more than 20%. In this case we are not able to test if the Jensens's alphas are zero, because the intercept is partially unobservable as a result of the transformation from (2.7), in which expected returns are linear in two betas: one that is induced by the covariance between returns and the pricing kernel and the other induced by the covariance between the conditional beta and the conditional consumption price of risk, to the linear relation between expected returns and the two unconditional betas given in (2.14).

Unlike the unconditional models, the performance of the models now improves monotonically as the data frequency decreases. Using monthly estimates, the Fama-French model shows the highest R^2, although the differences between the three models are small. Also, both the CAPM and the Fama-French model yield negative market risk premiums, while the CCAPM implies a positive premium at all frequencies. For quarterly and yearly estimates, the CCAPM shows the best performance by far, with consistently positive consumption premiums λ_c. The explanatory power of the CCAPM is the highest for the yearly estimates (60%), but the difference with the quarterly estimates is small. The estimated consumption risk premium and the implied risk aversions are close to the ones in Table 2.5.

When we use yields as the expected return measure, a similar pattern arises as for the unconditional results in Table 2.5. All models show the best performance again using quarterly estimates, and the Fama-French model achieves the highest R^2 at every frequency. However, as with the unconditional model, the conditional CAPM and the Fama-French model always yield negative market risk premiums λ_{mkt}, while the consumption model premiums are positive for both the quarterly and the yearly estimates. Similarly to the unconditional case, models estimated on yield-based expected returns produce lower pricing errors (i.e., CCAPM 2.6%, CAPM 2.4%, and FF model 2.2%) than those estimated with return-based expected returns (i.e., 2.8%, 3.7%, and 3.5% respectively). For the return-based measure of expected returns the CCAPM outperforms the other model when looking at pricing errors.

2.5.3 Ultimate consumption risk

As the previous results indicate that the horizon over which consumption is measured clearly matters, Table 2.7 reports the performance of the (unconditional) CCAPM based on ultimate consumption risk (Parker and Julliard (2005)) for different horizons S as defined in (2.13).[14] This separates out the frequency effects of consumption from futures returns, as the latter are measured at a constant frequency in the ultimate consumption risk model. Panel A shows the results using the mean futures returns again, and Panel B the results using the mean yields as the dependent variable in the cross-sectional regression. First, the results based on monthly mean returns indicate that the R^2 first increases until the horizon is about seven months, and then starts to decrease. However, the monthly mean returns almost invariably yield negative market prices of consumption risk. For the quarterly and annul returns the price of consumption risk is always positive, but here our results are contradictory to those of Parker and Julliard (2005). Where Parker and Julliard find an increasing performance as the number of quarters increases, we find the best performance for the contemporaneous first quarter, after which the performance of the ultimate risk measure deteriorates. Using yields as the expected return measure confirms this finding and even produces negative prices of consumption risk for longer horizons S. We also find that the best fit for monthly data at the horizon of seven months, does not correspond to the results for quarterly data, where the best fit appears for the contemporaneous quarter. This is likely to be a result of the differences in the measurement errors in consumption data across frequencies.

The results for the conditional CCAPM with ultimate consumption risk (Table 2.8) basically show the same pattern. As in the previous tables, the performance of the conditional model improves significantly on the unconditional one. However, the main finding for the ultimate risk is similar to the one in Table 2.6: after the first contemporaneous quarter (year), the performance of the model actually decreases by increasing the ultimate risk horizon, rather than increasing as in Parker and Julliard (2005).

2.5.4 Demand and supply factors

The difference in the performance of the ultimate risk for our futures data relative to stock market data needs further analysis.[15] As outlined in Breeden (1980) commodity betas may depend on their supply and demand elasticities and the covariances of goods' production with aggregate consumption. For instance, a positive demand shock will for many commodities lead to higher prices, but will also be associated with higher con-

[14] The results for the contemporaneous case (S=0) differ slightly from the ones reported in Table 2.5, because the sample period for returns is shorter as we use future consumption growth.

[15] Note that our results appear to be robust with respect to the sample period, the sample size, the consumption measure, the use of real or nominal series (these auxiliary results are available from the authors on request).

sumption, implying a positive short term beta. Following the demand shock however, demand may lower (because of a negative price elasticity) and supply may gradually increase, which both have off-setting effects on the relation between commodity prices on the one hand and longer term consumption on the other hand. Similarly, following a positive supply shock, prices will decrease and consumption will increase, leading to a negative short-term beta. Again, changes in demand and supply for the commodity following the price change will have off-setting effects in the longer run. Furthermore, French (1986) pointed out that demand and supply shocks to the current output are transmitted to future periods through inventories. The change in inventories is spread between consumption and storage, hence only part of the shock will affect future consumption.

Figure 2.3 provides some support for this, based on the consumption betas of our futures contracts. For each futures contract, the figure plots the beta with respect to the contemporaneous quarter consumption growth, as well as with respect to longer horizon consumption growth. For almost every futures contract the betas decrease in absolute value as the horizon increases, basically fading out to zero. This is consistent with the hypothesis formulated above that for commodities - which are part of aggregate consumption - supply and demand changes induce short term consumption betas, but basically zero longer term consumption betas. This may also explain the fact that in Tables 2.5 and 2.6 we find the strongest relation between consumption growth and futures returns at the quarterly horizon and not at the annual horizon: decreasing the frequency of returns and consumption growth from monthly to quarterly reduces the estimation error in consumption data, but a further decrease in the frequency actually decreases the performance because of the changing consumption betas.

To verify whether it is supply that off-sets the consumption adjustments, we estimate the two-factor investment-based asset pricing model as outlined in Cochrane (1991, 1996):

$$\begin{aligned} E[r_{i,t+1}] &= \lambda_0 + \lambda_{nr}\beta_{i,nr} + \lambda_r\beta_{i,r} \\ [\beta_{i,nr};\beta_{i,r}] &= \left[\frac{Cov\left[r_{i,t+j},\Delta i^S_{nr,t+j}\right]}{Var\left[\Delta i^S_{nr,t+j}\right]};\frac{Cov\left[r_{i,t+j},\Delta i^S_{r,t+j}\right]}{Var\left[\Delta i^S_{r,t+j}\right]}\right] \end{aligned} \tag{2.24}$$

where $\Delta i^S_{nr,t+j}$ is the growth rate of the non-residential investments, and $\Delta i^S_{r,t+j}$ is the growth rate in the residential investments (derived from the NIPA tables).[16] Similar

[16]In a pure production-based model firms remove arbitrage opportunities between asset returns and investment returns (producers' marginal rates of transformation). This implies the existence of the

to ultimate consumption risk, we conjecture that production or investment may react only slowly to commodity price changes, implying that an ultimate investment growth measure (analogous to the ultimate consumption growth measure described above), may better explain futures returns than contemporaneous investment growth. Table 2.9 supports this. For instance, based on quarterly returns, we see that the cross-sectional R^2 of the investment-based asset pricing model first increases until two quarters following the futures return, and then starts to decrease again. This pattern shows up when using mean futures returns and yields as expected return measures.

The impact of this slow production adjustment on consumption betas depends not only on supply elasticities but also on the covariances of goods' production with aggregate consumption. To see this, we estimate the consumption model controlling for changes in production. The additional variables are derived from the two-factor investment-based asset pricing model and are modeled by growth in both residential and non-residential investments. Based on the estimation from the 'ultimate' investment model (see Table 2.9) we use three quarter investment growth rates:[17]

$$E[r_{i,t+1}] = \lambda_0 + \lambda\beta, \tag{2.25}$$

where the vector β consists of the three betas defined in the following way:

$$\begin{aligned}\beta &= Cov(f, f')^{-1}Cov(f, r_{i,t+j}),\\ f &= (\Delta c^S_{t+j}, \Delta c^S_{t+j}\Delta i^3_{nr,t+j}, \Delta c^S_{t+j}\Delta i^3_{r,t+j}),\end{aligned}$$

and Δi^3_{nr} is the three quarter growth rate of the non-residential investments, and Δi^3_r is the three quarter growth rate in the residential investments.

Table 2.10 presents the results. For instance, based on quarterly returns, we see that the cross-sectional R^2 first increases until three quarters following the futures return, and then starts to decrease again when mean futures returns are used as the expected return measure. For yield-based expected returns the cross-sectional R^2s are increasing with the horizon. This is in line with the conjecture that for commodities supply changes have a direct impact on commodity prices and consumption adjustments, since part of the commodities are (strongly related to) consumption goods. Moreover, since this is

stochastic discount factor linear in both asset and investment returns. The above investment-based model is obtained by restricting the stochastic discount factor implied by the pure production-based model to be linear in investment returns only, i.e. it tests the hypothesis that investment returns are factors for asset returns.

[17]We also experiment with other horizons, but our results are robust with respect to the choice of the horizon.

an inherent feature of commodities we expect that in general it will not be true for the stock market, where supply changes are not directly related to the the consumption decisions. To see this we replicate the results in Parker and Julliard (2005) on the 25 FF portfolios. These results are available from the authors on request. We find that the longer horizon consumption $\beta's$ also decrease with the horizon but less sharply than our futures' consumption $\beta's$. Additionally, we estimate on their sample the consumption model controlling for production and we find that the production adjustments do not significantly affect the ultimate consumption risk.

To assess the robustness of our results, we also estimate the supply and demand elasticity directly from the aggregate demand and supply data. We assume a constant elasticity function and estimate elasticity using regressions of log demand (supply) on log prices:

$$\begin{aligned} \Delta log D_{i,t}^S &= \alpha_D + \beta_{D,i} \Delta log P_{i,t} + u_{i,t}, \\ \Delta log S_{i,t}^S &= \alpha_S + \beta_{S,i} \Delta log P_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{2.26}$$

where change in demand and supply is measured over different horizons S: $\Delta log I_{i,t}^S = log(\frac{I_{i,t+1+S}}{I_{i,t}})$ with $I_{i,t}^S = \{D_{i,t}^S, S_{i,t}^S\}$. We report the estimates of the slope coefficients and their standard errors in Table 2.11. For demand we use our consumption data, and for supply we use the Industrial Production Index (derived from the Federal Reserve Board). The demand elasticity remains small and insignificant across all considered horizons (i.e., on average it decreases from 0.15% to -0.15% during 4 quarters), while the supply elasticities are large and significant and they increase sharply with the horizon (i.e., on average by ten percentage points per year). This is in line with the aforementioned theoretical hypotheses of Breeden (1980) and is consistent with the results for the investment-based models (Tables 2.9 and 2.10). Also noticeable is the fact that the highest and actually increasing demand elasticity is found for futures on S&P 500 Index, which is in line with slow consumption adjustment to the shocks in stock returns as found in Parker and Julliard (2005).

Thus, to the extent that commodity price changes are followed by changes in demand and supply, this may explain why ultimate consumption risk is not as good a risk measure for commodities as for stocks.

2.6 Summary and Conclusions

Recent studies on consumption based models show that measuring consumption growth and/or returns over longer horizon improves the performance of the CCAPM in explaining the cross-sectional variation of expected stock returns. Drawing on these results, we study whether excess returns on futures contracts vary in a systematic way due to differences in consumption risk similarly to the returns on stocks. Historically, commodity futures have earned excess returns similar to those of equities (Gorton and Rouwenhorst (2006)). Nevertheless, they fulfill a different economic function than corporate securities such as stocks, i.e. they do not represent claims against future cash flows of the firm, but bets on the future expected spot prices of commodities. They also constitute a broader class of assets than simply stock returns, since they have as the underlying securities various commodities (agriculturals, meats, energy and precious metals), as well as currencies and an equity index.

In this chapter, we show that, similarly to stock returns, the (unconditional) CCAPM explains about 50 percent of the cross-sectional variation in mean futures returns at the quarterly frequency, while there is almost no explained variance at the monthly level, and an intermediate result at the yearly level. The conditional model yields even better performance than the unconditional model (i.e., the R^2 is about 60 percent) and, again, it is best at the quarterly and annual frequency. This pattern is consistent with the results found by Jagannathan and Wang (2005) based on stock portfolios, however we find somewhat lower implied consumption risk premiums for our futures contracts. In both cases, the CCAPM explains the futures returns better than either the CAPM or the Fama-French model.

Using the average yield as the measure of expected returns in the cross-sectional regression confirms that the CCAPM performs best at the quarterly frequency. However, the model can explain only up to 29 percent of the cross-sectional variation in yields in the unconditional case and up to 36 percent in the conditional case. The Fama-French model can explain the cross-sectional variation in yields much better (up to 45 and 55 percent respectively), but yields negative estimates of the market risk premia.

Finally, using ultimate consumption risk, we find that the performance of the CCAPM is best using consumption growth of the contemporaneous quarter of the returns, but then deteriorates for the longer horizons. Although this contradicts the findings of Parker and Julliard (2005) for stock returns, it is consistent with the finding that the CCAPM performs best at the quarterly frequency and may be the result of supply and demand elasticities of many of the commodities that underlie our futures contracts, inducing time-varying consumption betas. Indeed, we find that for commodities supply have an impact on commodity prices and therefore on consumption which violates the ultimate consumption risk measure. Moreover, we show that this is an inherent feature of commodities and in general it will not be true for the stock market, where supply changes are not expected to be related to the the consumption decisions. Future research should address the effect of supply and demand changes on expected futures returns more carefully.

2.A The conditional Consumption CAPM

This section repeats the proof of Theorem 1 from Jagannathan and Wang (1996) but in terms of the conditional CCAPM instead of their conditional CAPM. The proof proceeds in two steps:

1. If betas vary over time, then $(\beta_{ic}, \beta_{i\varphi})$ is a linear function of $(\overline{\beta}_{ic}, \varphi_{ic})$.
2. When $\beta_{i\varphi}$ is not linear in β_{ic} (i.e. when single beta CCAPM does not hold unconditionally, even though it holds conditionally), then expected returns are linear in $(\overline{\beta}_{ic}, \varphi_{ic})$ as well as in $(\beta_{ic}, \beta_{i\varphi})$.

Ad. 1 Define the return on a portfolio that is perfectly correlated with consumption as $r_{c,t+1}$. Then, note that for this portfolio the conditional CCAPM implies:

$$\begin{aligned} E_t[r_{c,t+1}] &= \lambda_{0c,t} + \lambda_{1c,t} \\ \lambda_{1c,t} &= E_t[r_{c,t+1} - \lambda_{0c,t}]. \end{aligned}$$

Define $\varepsilon_{i,t+1}$ as

$$\varepsilon_{i,t+1} = r_{i,t+1} - \lambda_{0c,t} - (r_{c,t+1} - \lambda_{0c,t})\beta_{ic,t}. \tag{2.27}$$

This implies the following orthogonality conditions:

$$\begin{aligned} E[\varepsilon_{i,t+1}] &= 0 \\ E[\varepsilon_{i,t+1} r_{c,t+1}] &= 0 \\ E[\varepsilon_{i,t+1} \lambda_{1c,t}] &= 0. \end{aligned}$$

We can substitute equation (2.6) into (2.27) to obtain

$$r_{i,t+1} = \lambda_{0c,t} + (r_{c,t+1} - \lambda_{0c,t})\overline{\beta}_{ic} + (r_{c,t+1} - \lambda_{0c,t})(\lambda_{1c,t} - \lambda_{1c})\varphi_{ic} + (r_{c,t+1} - \lambda_{0c,t})\eta_{ic,t} + \varepsilon_{i,t+1}$$

From the definition of covariance and the orthogonality conditions given above we obtain

$$\begin{aligned} Cov(r_{i,t+1}, \Delta c_{t+1}) &= Cov(r_{i,t+1}, r_{c,t+1}) \qquad (2.28) \\ &= Cov(\lambda_{0c,t}, r_{c,t+1}) + Cov(r_{c,t+1} - \lambda_{0c,t}, r_{c,t+1})\overline{\beta}_{ic} \\ &+ Cov((r_{c,t+1} - \lambda_{0c,t})(\lambda_{1c,t} - \lambda_{1c}), r_{c,t+1})\varphi_{ic} + Cov((r_{c,t+1} - \lambda_{0c,t})\eta_{ic,t}, r_{c,t+1}), \\ Cov(r_{i,t+1}, \lambda_{1c,t}) &= Cov(\lambda_{0c,t}, \lambda_{1c,t}) + Cov(r_{c,t+1} - \lambda_{0c,t}, \lambda_{1c,t})\overline{\beta}_{ic} \qquad (2.29) \\ &+ Cov((r_{c,t+1} - \lambda_{0c,t})(\lambda_{1c,t} - \lambda_{1c}), \lambda_{1c,t})\varphi_{ic} + Cov((r_{c,t+1} - \lambda_{0c,t})\eta_{ic,t}, \lambda_{1c,t}). \end{aligned}$$

Since, for the CCAPM $\beta_{ic} = \frac{Cov(r_{i,t+1}, \Delta c_{t+1})}{Var(\Delta c_{t+1})}$ and $\beta_{i\varphi} = \frac{Cov(r_{i,t+1}, \lambda_{1c,t})}{Var(\lambda_{1c,t})}$, these equations imply that $(\beta_{ic}, \beta_{i\varphi})$ will be a linear function of $(\overline{\beta}_{ic}, \varphi_{ic})$, if the last terms in both equations (2.28) and (2.29) are zero. Hence, we assume that the residual $\eta_{ic,t}$ from the projection equation (2.6) satisfies the following orthogonal conditions:

$$\begin{aligned} E[\eta_{ic,t} E_t[r_{c,t+1}]] &= 0 \\ E[\eta_{ic,t} \lambda^2_{1c,t}] &= 0 \\ E[\eta_{ic,t} \lambda_{1c,t} \lambda_{0c,t}] &= 0. \end{aligned}$$

This completes step 1.

Ad. 2 From step 1 we know that

$$\begin{pmatrix} \beta_{ic} \\ \beta_{i\varphi} \end{pmatrix} = \begin{pmatrix} b_0 \\ c_0 \end{pmatrix} + \begin{pmatrix} b_1 & b_2 \\ c_1 & c_2 \end{pmatrix} \begin{pmatrix} \overline{\beta}_{ic} \\ \varphi_{ic} \end{pmatrix}. \tag{2.30}$$

To show that $(\overline{\beta}_{ic}, \varphi_{ic})$ are linear in $(\beta_{ic}, \beta_{i\varphi})$ we need to show that equation (2.30) is invertible. Suppose that the 2 by 2 matrix in this equation is singular, then there is a nonzero vector (x, y) such that

$$(x, y) \begin{pmatrix} b_1 & b_2 \\ c_1 & c_2 \end{pmatrix} = 0,$$

which implies that $x\beta_{ic} + y\beta_{i\varphi}$ is a constant across securities. Since β_{ic} is not a constant across assets, we must have $y \neq 0$ for singularity to hold. In this case $\overline{\beta}_{ic}$ will be linear in φ_{ic} and hence both β_{ic} and $\beta_{i\varphi}$ will be linear in $\overline{\beta}_{ic}$ only. But this contradicts the initial assumption of non-linearity between $\beta_{i\varphi}$ and β_{ic} and hence this 2 by 2 matrix must be invertible. Now we can invert equation (2.30) such that $(\overline{\beta}_{ic}, \varphi_{ic})$ are linear in $(\beta_{ic}, \beta_{i\varphi})$ and substitute them into (2.7) to obtain (2.9), which completes step 2 and the proof.

2.B Estimation error in the intercept

Recall that when we assume that returns and consumption growth are jointly log-normally distributed then the unconditional model in (2.12) implies that the expected log (excess) returns are linear in consumption betas:

$$E\left[r_{f,i,t+j}\right] = \lambda_0 + \lambda_c \beta_{ic,j},$$

where $\lambda_0 = -0.5Var\left(r_{f,i,t+1}\right).$ Thus, in order to test if Jensen's alpha is zero we need to incorporate the estimation error in $Var\left(r_{f,i,t+1}\right).$ Note that for futures returns we can rewrite the LHS in the following way:

$$E\left[r_{f,i,t+j}\right] + 0.5Var\left[r_{f,i,t+j}\right] = \log\left\{E\left[R_{f,i,t+j}\right]\right\},$$

where $r_{f,i,t+j}$ is defined in (2.19) and $R_{f,i,t+j} = \exp\left(r_{f,i,t+j}\right) = \frac{P_{t+1}}{F_t}$. Hence, to test if Jensen's alpha is zero in the unconditional models we can estimate the cross-sectional regression using $\log\left\{E\left[R_{f,i,t+j}\right]\right\}$as a dependent variable and test the hypothesis that the intercept is zero.

2.C Log-linearization for ultimate risk horizon

The assumption on joint log-normality of consumption growth and returns implies the following for expected returns:

$$E\left[r_{i,t+j}\right] = -\log\delta + \gamma E\left[\log\left(\frac{C_{t+j}}{C_t}\right)\right] + 0.5\left(\sigma_i^2 + \gamma^2\sigma_c^2 - 2\gamma\sigma_{ic}\right).$$

Next, consider the excess returns on the securities of the following form:

$$E\left[r_{i,t+j} - r_t^f\right] = -0.5Var\left[r_{i,t+j}\right] + \gamma Cov\left[r_{i,t+j}, \log\left(\frac{C_{t+j}}{C_t}\right)\right]. \tag{2.31}$$

Assuming that the the risk free rate of borrowing between time $t+1$ and $t+1+S$ is constant so that the consumption-CAPM holds in the following way:

$$E\left[r^f_{t+j,t+j+S}\right] = -\log\delta + \gamma_S E\left[\log\left(\frac{C_{t+j+S}}{C_{t+j}}\right)\right] + 0.5\gamma_S^2\sigma_{c,S}^2,$$

allows us to substitute out C_{t+j} in (2.31) and obtain:

$$E\left[r_{i,t+j} - r_t^f\right] + 0.5Var\left[r_{i,t+j}\right] = \gamma Cov\left[r_{i,t+j}, \log\left(\frac{C_{t+j+S}}{C_t}\right)\right] - \theta,$$

where $\theta = \frac{\gamma}{\gamma_S} Cov\left[r_{i,t+j}, r^f_{t+j,t+j+S} + \log\delta - 0.5\gamma_S^3\sigma_{c,S}^2\right]$ which is assumed to be zero. It follows immediately, that we can use the beta representation of the form:

$$\begin{aligned} E\left[r_{i,t+j}\right] &= \lambda_0 + \lambda_c\beta_{ic,j}, \\ \beta_{ic,j} &= \frac{Cov\left[r_{i,t+j}, \Delta c^S_{t+j}\right]}{Var\left[\Delta c^S_{t+j}\right]}. \end{aligned}$$

where $\Delta c^S_{t+j} = \log\left(\frac{C_{t+j+S}}{C_t}\right)$.

2.D Figures and Tables

Table 2.1: **Historical growth rates in futures yields.**

The table gives the estimates of the annual average growth rates in convenience yields for 25 futures contracts. The sample period varies across futures. The end of the sample period is always December 2004. The earliest starting date is February 1968 which gives 442 observations, and the latest is October 1988 with 194 observations. The details on the exact starting dates for each futures contract are given in Table 2.3. From equation (2.17) the per-period yields are computed as the log price differences between the nearest-to-maturity contracts and the ones that are closest to having a maturity 12 months longer than the nearest-to-maturity contracts correcting for the varying length of spread. Then, from equation (2.18) the convenience yields are computed by correcting the yields with the interest rate over the same spread. Finally, the table reports the average growth rates in convenience yields, their standard errors and the t-statistics for testing the significance of means. Newey-West standard deviations are used.

Futures contract	Averages	Standard deviations	t-statistics
	Commodities		
Grains			
Wheat	3.16%	34.72%	(0.61)
Corn	2.86%	36.15%	(0.51)
Oats	-0.47%	47.63%	(-0.07)
Oil & Meal			
Soybean	4.66%	40.29%	(0.79)
Soybeans Oil	4.60%	42.92%	(0.73)
Soybean meal	1.97%	46.11%	(0.28)
Meats			
Live cattle	2.88%	30.84%	(0.96)
Feeder cattle	3.77%	22.53%	(1.12)
Live (lean) hog	3.27%	57.94%	(0.44)
Pork Bellies	2.55%	66.40%	(0.33)
Energy			
Crude Oil	1.73%	52.28%	(0.19)
Heating Oil	0.79%	48.54%	(0.11)
Unleaded Gas	1.95%	57.72%	(0.22)
Metals			
Gold	2.87%	20.06%	(0.67)
Silver	4.03%	32.99%	(0.72)
Platinum	5.05%	30.11%	(1.02)
Copper	0.62%	33.79%	(0.08)
Food/Fiber			
Coffee	-0.08%	48.13%	(-0.01)
Sugar	-6.86%	59.10%	(-0.65)
Cotton	1.37%	47.51%	(0.19)
	Financials		
Index			
S&P 500	9.54%	15.03%	(2.86)
Foreign Currency			
Japanese Yen	3.54%	13.55%	(1.30)
British Pound	-0.46%	11.95%	(-0.21)
Candian $	-1.00%	6.26%	(-0.87)
Swiss Frank	2.45%	13.78%	(0.91)

Table 2.2: **The relation between mean returns and yields.**

This table reports the estimates from the cross-sectional regression of 25 futures log mean returns ($\overline{r}_{f,i,t+1}$) on log mean yields ($\overline{y}_{i,t}$):

$$\overline{r}_{f,i} = \alpha + \beta \overline{y}_i + u_i$$

The sample period varies across futures. The end of the sample period is always December 2004. The earliest starting date is February 1968 which gives 442 observations, and the latest is October 1988 with 194 observations. The details on the exact starting dates for each futures contract are given in Table 2.3. The yields are computed as the log price difference between the nearest-to-maturity contracts and the ones that are closest to having a maturity 12 months longer than the nearest-to-maturity contracts, correcting for the varying length of spread. In a regression without a constant the uncentered R^2 is reported. Fama-MacBeth standard errors are reported in the second row, and Shanken corrected standard errors are in the third row.

	Intercept	Slope	R^2
Coefficient	0.026	1.09	61.30
Standard error	(0.017)	(0.38)	
Corrected error	(0.018)	(0.40)	
Coefficient		0.88	42.51
Standard error		(0.39)	
Corrected error		(0.40)	

Table 2.3: **Futures contracts.**

The table reports the futures exchange, the delivery months, and the beginning date of the sample period for the 25 futures contracts in our sample. The end date of the sample period, December 2004, is common for all contracts.

Futures contract	Exchange	Delivery months	Start date
	Commodities		
Grains			
Wheat	Chicago Board of Trade	3,5,7,9,12	1968 Dec
Corn	Chicago Board of Trade	3,5,7,9,12	1968 Dec
Oats	Chicago Board of Trade	3,5,7,9,12	1974 Dec
Oil & Meal			
Soybean	Chicago Board of Trade	1,3,5,7,8,9,11	1968 Nov
Soybeans Oil	Chicago Board of Trade	1,3,5,7,8,9,10,12	1968 Nov
Soybean meal	Chicago Board of Trade	1,3,5,7,8,9,10,12	1968 Nov
Meats			
Live cattle	Chicago Mercantile Exchange	2,4,6,8,10,12	1976 Dec
Feeder cattle	Chicago Mercantile Exchange	1,3,4,5,8,9,10,11	1977 Oct
Live (lean) hog	Chicago Mercantile Exchange	2,4,6,7,8,10,12	1969 Dec
Pork Bellies	Chicago Mercantile Exchange	2,3,5,7,8	1969 Aug
Energy			
Crude Oil	New York Mercantile Exchange	All	1983 Dec
Heating Oil	New York Mercantile Exchange	All	1979 Dec
Unleaded Gas	New York Mercantile Exchange	All	1985 Apr
Metals			
Gold	Commodity Exchange, Inc.	1,2,4,6,8,10,12	1975 Jan
Silver	Commodity Exchange, Inc.	3,5,7,9,12	1968 Feb
Platinum	New York Mercantile Exchange	1,4,7,10	1972 Sep
Copper	Commodity Exchange, Inc.	1,3,5,7,9,12	1988 Oct
Food/Fiber			
Coffee	New York Board of Trade	3,5,7,9,12	1973 Dec
Sugar	New York Board of Trade	3,5,7,10	1974 Oct
Cotton	New York Board of Trade	3,5,7,10,12	1972 Dec
	Financials		
Index			
S&P 500	International Monetary Market	3,6,9,12	1982 Dec
Foreign Currency			
Japanese Yen	International Monetary Market	3,6,9,12	1976 Dec
British Pound	International Monetary Market	3,6,9,12	1975 Dec
Candian $	International Monetary Market	3,6,9,12	1977 Dec
Swiss Frank	International Monetary Market	3,6,9,12	1975 Dec

Table 2.4: **Descriptive statistics.**

The table gives the descriptive statistics for the 25 futures contracts, consumption growth and benchmark factors. The sample period varies across futures (see Table 2.3). The yields are computed as the log price difference between the nearest-to-maturity contracts and the ones that are closest to having a maturity 12 months longer than the nearest-to-maturity contracts. To correct for the varying length of spread we use yields projected on the maturity equal exactly 12 months. Hence, the standard errors reported in the last column, correspond to the standard errors of these forecasted yields. Panel A describes the statistics for expected returns estimated from data for different frequency: monthly (M), quarterly (Q) and yearly (Y). Panels B and C give the same statistics for consumption growth and returns on the benchmark factors respectively.

	Annualized returns						Annualized	
	Mean in %			Standard Deviation			Yields	
	M	Q	Y	M	Q	Y	Mean in %	St. Dev
				Panel A: epxected returns				
Futures contract								
Wheat	-2.38	-1.96	0.16	23.8	26.3	34.9	-3.55	10.17
Corn	-4.58	-4.08	-3.28	23.6	25.3	28.5	-4.45	9.49
Oats	-8.17	-7.70	-7.09	29.4	31.8	32.6	-7.71	12.43
Soybean	0.57	0.61	0.81	27.1	28.6	28.0	-0.71	10.25
Soybeans Oil	3.97	3.52	6.77	31.1	31.3	45.0	-1.63	10.41
Soybean meal	2.06	2.43	2.85	29.8	31.4	32.4	-0.15	12.50
Live cattle	5.20	5.36	4.96	15.5	15.0	14.9	-0.28	6.17
Feeder cattle	3.96	4.14	3.33	14.9	15.3	19.7	-0.05	4.31
Live hog	3.12	2.76	1.66	26.9	27.0	26.3	1.53	16.05
Pork Bellies	-4.04	-5.22	-8.85	35.1	33.6	25.9	-4.90	13.23
Crude Oil	10.67	13.03	11.70	32.8	38.5	44.4	6.31	11.71
Heating Oil	4.15	6.24	4.42	30.3	34.3	35.2	3.37	11.02
Unleaded Gas	13.85	14.53	14.09	33.7	34.5	38.2	7.13	11.83
Gold	-3.16	-3.61	-2.71	19.4	19.4	28.8	-6.42	3.86
Silver	-3.59	-4.82	-1.04	31.7	32.1	58.4	-6.92	3.92
Platinum	2.44	1.37	1.92	28.9	25.3	32.0	-5.68	3.81
Copper	6.14	6.07	2.68	24.1	25.0	29.1	3.72	12.82
Coffee	0.85	1.49	3.52	38.3	44.5	53.1	-2.16	13.58
Sugar	-10.59	-9.22	-11.94	39.8	43.1	37.7	-3.13	15.12
Cotton	-0.01	0.23	4.26	24.6	26.8	38.6	-0.09	11.89
S&P 500	6.74	6.89	7.23	14.8	16.5	16.5	-3.03	1.89
Japanese Yen	0.46	0.26	0.52	12.8	14.1	16.2	-3.17	1.73
British Pound	1.87	1.59	1.90	10.9	11.1	15.4	1.70	1.39
Candian $	0.54	0.23	0.20	5.6	5.6	7.4	0.86	1.24
Swiss Frank	-0.29	-0.55	-0.59	13.0	14.4	15.9	-3.06	2.12
				Panel B: consumption growth				
Consumption growth	2.08	2.07	2.04	1.2	0.8	1.1		
				Panel C: benchmark factors				
MKT	5.35	5.68	5.48	16.0	18.0	18.3		
SMB	2.08	2.73	1.95	11.5	12.1	13.2		
HML	5.37	5.26	5.90	10.7	12.4	15.2		

Table 2.5: **Unconditional models.**

The table reports the cross-sectional regression estimation results for the Consumption CAPM model and the two benchmark models: the CAPM and the Fama-French three factor model:

$$E[r_{i,t+1}] = \lambda_0 + \lambda\beta_i$$

where β_i is the time-series futures returns loadings on consumption growth (CCAPM), or on the excess return on the market portfolio (CAPM), or on the three Fama-French factors (Three factor model). We use 25 futures contracts with varying sample period (see Table 2.3). In Panel A expected returns are measured as the historical means of futures returns, while in Panel B yield-based expected returns are used. γ is the implied coefficient of risk aversion defined as $\frac{\lambda_c}{Var[\Delta c_{t+1}]}$. The first row reports the coefficient estimates. Fama-MacBeth standard errors are reported in the second row, and Shanken corrected standard errors are in the third row. Below the sample R^2's we report the 95% confidence intervals based on the 10000 Monte Carlo simulations. The significance level of the intercept takes into account the estimation error in $Var(r_{i,t+1})$ (see Appendix 2.B for details). */** indicates significance level at 10/5 percent.

	CCAPM				CAPM			Three factor model				
	λ_0	λ_c	$R^2_{(adj)}$	γ	λ_0	λ_{mkt}	$R^2_{(adj)}$	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	$R^2_{(adj)}$
						Panel A : mean returns						
						monthly						
Coeff	4.11**	1.03	2.55%	343	4.89**	-2.72	1.05%	4.82**	-2.18	1.41	-0.89	1.21%
St err	(1.33)	(1.33)	[0.01;29.65]		(1.20)	(5.51)	[0.00;17.37]	(1.34)	(6.04)	(9.45)	(9.27)	[1.20;45.61]
Corr err	(1.50)	(1.10)	-1.69%		(1.85)	(4.58)	-3.25%	(1.87)	(5.16)	(9.51)	(9.90)	-12.90%
			[-4.34;26.59]				[-4.34;13.78]					[-12.99;37.83]
						quarterly						
Coeff	3.04	1.04**	50.72%	146	4.68**	-8.21	18.25%	5.28**	-8.46	-8.79	6.91	26.27%
St err	(0.91)	(0.21)	[0.72;61.86]		(1.11)	(3.62)	[0.01;25.04]	(1.19)	(3.57)	(4.45)	(6.42)	[2.35;57.93]
Corr err	(2.21)	(0.47)	48.58%		(1.82)	(4.33)	14.70%	(2.15)	(5.20)	(5.71)	(8.52)	15.74%
			[-3.60;60.20]				[-4.34;21.78]					[-11.48;51.92]
						yearly						
Coeff	1.96	0.84**	35.27%	29	5.43**	0.42	0.08%	5.26**	-0.07	1.54	-0.31	2.38%
St err	(1.24)	(0.24)	[0.05;55.39]		(1.27)	(3.01)	[0.01;25.04]	(1.36)	(3.26)	(2.50)	(3.67)	[1.88;49.60]
Corr err	(2.36)	(0.36)	32.45%		(1.81)	(2.56)	-4.26%	(4.08)	(5.74)	(5.02)	(9.04)	-11.57%
			[-4.30;53.46]				[-4.34;21.78]					[-12.14;42.40]
						Panel B: yields						
						monthly						
Coeff	-1.52	-0.42	0.83%	-842	-1.49	-4.88	6.58%	-1.22	-4.94	-4.41	-1.19	9.84%
St err	(0.95)	(0.96)	-3.48%		(0.83)	(3.83)	2.52%	(0.92)	(4.13)	(6.46)	(6.34)	-3.04%
Corr err	(1.61)	(1.34)			(2.07)	(5.00)		(2.10)	(5.11)	(12.12)	(12.43)	
						quarterly						
Coeff	-2.68	0.53	28.26%	117	-2.05	-6.00	21.84%	-1.41	-6.09	-9.23	4.64	45.29%
St err	(0.75)	(0.18)	25.14%		(0.72)	(2.37)	18.44%	(0.69)	(2.06)	(2.56)	(3.70)	37.47%
Corr err	(1.88)	(0.46)			(1.72)	(4.41)		(1.95)	(4.62)	(5.82)	(9.64)	
						yearly						
Coeff	-2.67	0.26	6.55%	15	-1.83	0.12	0.02%	-2.23	0.54	-1.25	-4.68	20.29%
St err	(1.06)	(0.20)	2.49%		(0.81)	(1.93)	-4.33%	(0.79)	(1.89)	(1.45)	(2.13)	8.91%
Corr err	(2.15)	(0.38)			(1.80)	(2.54)		(2.30)	(2.89)	(2.96)	(5.01)	

Table 2.6: **Conditional models.**

The table reports the cross-sectional regression estimation results for the Consumption CAPM model and the two benchmark models: the CAPM and the Fama-French three factor model:

$$E[r_{i,t+1}] = \lambda_0 + \lambda\beta_i + \lambda_{term}\beta_{i,term}$$

where β_i is the time-series futures returns loadings on consumption growth (CCAPM), or on the excess return on the market portfolio (CAPM), or on the three Fama-French factors (Three factor model). $\beta_{i,term}$ is the slope coefficient from a time-series regression of futures returns on the term structure variable that proxies for the time varying risk premiums. We use 25 futures contracts with varying sample period (see Table 2.3). In Panel A expected returns are measured as the historical means of futures returns, while in Panel B yield-based expected returns are used. γ is the implied coefficient of risk aversion defined as $\frac{\lambda_c}{Var[\Delta c_{t+1}]}$. The first row reports the coefficient estimates. Fama-MacBeth standard errors are reported in the second row, and Shanken corrected standard errors are in the third row. Below the sample R^2's we report the 95% confidence intervals based on the 10000 Monte Carlo simulations.

	conditional CCAPM					conditional CAPM				conditional Three factor model					
	λ_0	λ_c	λ_{term}	R^2 (R^2_{adj})	γ	λ_0	λ_{mkt}	λ_{term}	R^2 (R^2_{adj})	λ_0	λ_{mkt}	λ_{smb}	λ_{hml}	λ_{term}	R^2 (R^2_{adj})
Panel A : mean returns															
monthly															
Coeff	3.78	0.21	15.35	23.02%	169	7.66	-5.19	16.65	20.21%	7.53	-4.42	3.98	0.98	17.54	21.54%
St err	(1.55)	(1.19)	(5.99)	[0.50;44.08]		(1.63)	(5.17)	(7.24)	[0.27;31.66]	(1.71)	(5.61)	(8.72)	(8.60)	(7.71)	[0.25;31.94]
Corr err	(1.67)	(1.17)	(8.19)	16.02%		(2.32)	(5.81)	(10.19)	12.96%	(2.37)	(6.15)	(11.06)	(11.41)	(10.11)	5.84%
				[-8.55;39.00]					[-8.80;25.45]						[-8.82;25.75]
quarterly															
Coeff	1.15	0.89	11.57	58.70%	505	7.23	-7.07	21.88	43.16%	7.37	-7.32	-5.61	5.52	20.06	45.65%
St err	(1.24)	(0.20)	(6.07)	[4.12;68.52]		(1.25)	(3.11)	(7.05)	[0.67;48.34]	(1.31)	(3.17)	(4.09)	(5.68)	(7.51)	[0.93;51.92]
Corr err	(1.75)	(0.45)	(9.59)	54.95%		(2.12)	(5.29)	(11.82)	37.99%	(2.22)	(5.14)	(5.86)	(9.35)	(11.31)	34.78%
				[-4.59;65.66]					[-8.36;43.64]						[-8.08;47.54]
yearly															
Coeff	0.56	0.65	38.58	60.21%	53	6.99	-0.75	37.34	30.12%	7.19	-0.98	0.00	1.68	39.01	30.92%
St err	(1.02)	(0.19)	(8.60)	[1.66;64.24]		(1.20)	(2.60)	(12.14)	[0.59;50.38]	(1.35)	(2.83)	(2.22)	(3.24)	(13.57)	[0.67;52.06]
Corr err	(1.89)	(0.33)	(22.90)	56.59%		(2.12)	(3.16)	(17.74)	23.77%	(2.17)	(3.12)	(2.57)	(5.19)	(15.10)	17.10%
				[-7.28;60.99]					[-8.45;45.87]						[-8.36;47.70]
Panel B: yields															
monthly															
Coeff	0.66	-0.14	10.70	21.94%	-113	0.96	-7.05	14.71	35.79%	0.98	-6.75	-2.29	0.22	14.17	35.83%
St err	(1.13)	(0.86)	(4.35)	14.85%		(1.05)	(3.32)	(4.65)	29.95%	(1.11)	(3.63)	(5.64)	(5.56)	(4.99)	23.00%
Corr err	(1.98)	(1.45)	(8.58)			(2.65)	(5.65)	(10.46)		(2.64)	(5.84)	(12.80)	(13.71)	(10.64)	
quarterly															
Coeff	-0.91	0.44	8.57	36.43%	249	-0.39	-5.26	14.28	45.60%	-0.24	-5.45	-7.45	3.87	11.20	58.82%
St err	(1.08)	(0.18)	(5.29)	30.65%		(0.82)	(2.03)	(4.61)	40.66%	(0.76)	(1.84)	(2.38)	(3.30)	(4.37)	50.58%
Corr err	(1.97)	(0.45)	(10.78)			(2.01)	(4.77)	(11.02)		(2.13)	(4.73)	(5.76)	(9.75)	(10.89)	
yearly															
Coeff	-0.87	0.26	26.27	36.26%	22	-1.11	-0.42	17.29	15.67%	-1.46	0.17	-1.87	-3.88	15.63	31.43%
St err	(0.98)	(0.18)	(8.30)	30.46%		(0.84)	(1.83)	(8.55)	8.00%	(0.86)	(1.81)	(1.42)	(2.07)	(8.67)	17.72%
Corr err	(2.14)	(0.41)	(17.52)			(1.91)	(2.66)	(13.75)		(2.10)	(2.64)	(2.84)	(4.32)	(13.75)	

Table 2.7: **Ultimate risk for unconditional consumption model.**

The table reports the cross-sectional regression estimation results for the Consumption CAPM:

$$E[r_{i,t+1}] = \lambda_0 + \lambda_1 \beta_i,$$

where β_i is the time-series futures returns loadings on consumption growth based on different horizons S: $\Delta c^S_{t+j} = \log\left(\frac{C_{t+j+S}}{C_t}\right)$. We use 25 futures contracts with varying sample period (see Table 2.3). In Panel A expected returns are measured as the historical means of futures returns, while in Panel B yield-based expected returns are used. γ is the implied coefficient of risk aversion defined as $\frac{\lambda_c}{Var\left[\Delta c^S_{t+1}\right]}$. We report Fama-MacBeth standard errors, and next to them Shanken corrected standard errors.

S	λ_0	St.err	Corr err	λ_1	St.err	Corr err	R^2	R^2_{adj}	γ
				Panel A: mean returns					
				monthly					
0	4.42	(1.30)	(1.52)	0.47	(1.30)	(1.17)	0.56%	-0.04	378
1	4.50	(1.31)	(1.63)	0.28	(1.19)	(1.02)	0.24%	-0.04	224
2	5.17	(1.19)	(1.75)	-1.00	(0.92)	(1.09)	4.85%	0.01	-703
3	5.13	(1.16)	(1.80)	-1.17	(1.00)	(1.15)	5.59%	0.01	-673
4	5.11	(1.12)	(1.83)	-1.42	(1.00)	(1.21)	7.98%	0.04	-686
5	4.98	(1.06)	(1.85)	-1.84	(0.99)	(1.30)	13.16%	0.09	-760
6	4.93	(1.04)	(1.86)	-2.16	(1.04)	(1.41)	15.73%	0.12	-774
7	4.80	(1.04)	(1.86)	-2.29	(1.12)	(1.49)	15.33%	0.12	-724
8	4.75	(1.05)	(1.86)	-2.37	(1.26)	(1.59)	13.31%	0.10	-662
9	4.68	(1.06)	(1.85)	-2.38	(1.39)	(1.66)	11.31%	0.07	-589
10	4.56	(1.07)	(1.84)	-2.37	(1.46)	(1.72)	10.23%	0.06	-526
11	4.56	(1.08)	(1.82)	-2.18	(1.57)	(1.79)	7.71%	0.04	-434
12	4.54	(1.09)	(1.81)	-2.08	(1.64)	(1.83)	6.55%	0.02	-375
				quarterly					
0	2.89	(0.81)	(2.23)	1.05	(0.19)	(0.48)	56.43%	0.55	585
1	3.43	(1.08)	(2.11)	1.06	(0.39)	(0.59)	24.17%	0.21	361
2	4.04	(1.16)	(1.98)	0.82	(0.57)	(0.68)	8.44%	0.04	194
3	4.26	(1.11)	(1.95)	0.96	(0.65)	(0.82)	8.53%	0.05	164
4	4.52	(1.10)	(1.88)	0.80	(0.72)	(0.87)	5.05%	0.01	106
				yearly					
0	2.21	(1.33)	(2.28)	0.74	(0.27)	(0.38)	24.42%	0.21	61
1	4.06	(1.16)	(2.03)	0.48	(0.35)	(0.46)	7.49%	0.03	25
				Panel B: yields					
				monthly					
0	-1.41	(0.89)	(1.53)	-0.71	(0.89)	(1.29)	2.69%	-0.02	-570
1	-1.20	(0.87)	(1.79)	-1.01	(0.79)	(1.09)	6.64%	0.03	-809
2	-0.99	(0.73)	(1.91)	-1.52	(0.57)	(1.09)	23.76%	0.20	-1070
3	-1.11	(0.72)	(1.94)	-1.63	(0.62)	(1.20)	22.87%	0.20	-937
4	-1.21	(0.69)	(1.92)	-1.77	(0.62)	(1.30)	26.15%	0.23	-855
5	-1.44	(0.66)	(1.85)	-1.90	(0.61)	(1.37)	29.78%	0.27	-786
6	-1.51	(0.65)	(1.84)	-2.09	(0.65)	(1.47)	31.30%	0.28	-751
7	-1.64	(0.64)	(1.81)	-2.24	(0.70)	(1.59)	30.99%	0.28	-708
8	-1.68	(0.65)	(1.80)	-2.39	(0.79)	(1.75)	28.63%	0.26	-668
9	-1.76	(0.66)	(1.79)	-2.48	(0.87)	(1.89)	26.12%	0.23	-616
10	-1.88	(0.67)	(1.76)	-2.54	(0.92)	(2.01)	24.90%	0.22	-565
11	-1.89	(0.68)	(1.75)	-2.54	(0.99)	(2.16)	22.08%	0.19	-506
12	-1.92	(0.69)	(1.74)	-2.53	(1.04)	(2.26)	20.50%	0.17	-457
				quarterly					
0	-2.65	(0.71)	(1.76)	0.52	(0.17)	(0.43)	28.94%	0.26	288
1	-2.11	(0.84)	(1.80)	0.29	(0.30)	(0.61)	3.84%	0.00	99
2	-1.74	(0.83)	(1.79)	-0.05	(0.41)	(0.80)	0.06%	-0.04	-11
3	-1.76	(0.80)	(1.74)	-0.03	(0.47)	(0.96)	0.02%	-0.04	-6
4	-1.74	(0.78)	(1.72)	-0.17	(0.51)	(1.07)	0.47%	-0.04	-22
				yearly					
0	-2.73	(1.01)	(2.03)	0.29	(0.21)	(0.38)	7.81%	0.04	24
1	-1.77	(0.83)	(1.86)	0.00	(0.25)	(0.52)	0.00%	-0.04	0

Table 2.8: **Ultimate risk for conditional consumption model.**

The table reports the cross-sectional regression estimation results for the conditional Consumption CAPM:

$$E[r_{i,t+1}] = \lambda_0 + \lambda_1 \beta_i + \lambda_{term} \beta_{i,term},$$

where β_i is the time-series futures returns loadings on consumption growth based on different horizons S: $\Delta c^S_{t+j} = \log\left(\frac{C_{t+j+S}}{C_t}\right)$. $\beta_{i,term}$ is the slope coefficient from a time-series regression of futures returns on the term structure variable that proxies for the time varying risk premiums. We use 25 futures contracts with varying sample period (see Table 2.3). In Panel A expected returns are measured as the historical means of futures returns, while in Panel B yield-based expected returns are used. γ is the implied coefficient of risk aversion defined as $\frac{\lambda_c}{Var\left[\Delta c^S_{t+1}\right]}$. We report Fama-MacBeth standard errors, and next to them Shanken corrected standard errors.

S	λ_0	St.err	Corr err	λ_1	St.err	Corr err	λ_{term}	St.err	Corr err	R^2	R^2_{adj}	γ
						Panel A: mean returns						
						monthly						
0	3.73	(1.45)	(1.77)	0.39	(1.15)	(1.21)	14.79	(5.52)	(7.98)	24.67%	0.18	314
1	3.55	(1.44)	(1.89)	0.78	(1.03)	(1.04)	15.15	(5.45)	(7.96)	26.18%	0.19	620
2	3.86	(1.40)	(1.87)	0.06	(0.86)	(1.08)	14.57	(5.73)	(7.62)	24.30%	0.17	45
3	3.86	(1.40)	(1.88)	0.01	(0.92)	(1.15)	14.44	(5.64)	(7.73)	24.28%	0.17	4
4	3.88	(1.39)	(1.86)	-0.26	(0.93)	(1.21)	14.06	(5.59)	(7.75)	24.55%	0.18	-125
5	3.80	(1.39)	(1.81)	-0.57	(0.94)	(1.29)	13.58	(5.57)	(7.74)	25.51%	0.19	-233
6	3.76	(1.39)	(1.80)	-0.74	(1.00)	(1.39)	13.38	(5.56)	(7.77)	26.09%	0.19	-264
7	3.72	(1.39)	(1.79)	-0.84	(1.07)	(1.47)	13.39	(5.52)	(7.86)	26.35%	0.20	-266
8	3.74	(1.40)	(1.79)	-0.79	(1.19)	(1.59)	13.58	(5.53)	(7.93)	25.75%	0.19	-220
9	3.75	(1.40)	(1.79)	-0.72	(1.29)	(1.68)	13.78	(5.52)	(7.99)	25.33%	0.19	-179
10	3.73	(1.41)	(1.79)	-0.70	(1.35)	(1.76)	13.88	(5.50)	(8.03)	25.19%	0.18	-156
11	3.78	(1.41)	(1.79)	-0.49	(1.43)	(1.84)	14.10	(5.50)	(8.06)	24.69%	0.18	-99
12	3.79	(1.41)	(1.80)	-0.45	(1.48)	(1.90)	14.18	(5.48)	(8.08)	24.60%	0.18	-81
						quarterly						
0	1.38	(1.06)	(1.60)	0.81	(0.18)	(0.42)	10.81	(4.69)	(8.85)	63.94%	0.61	451
1	2.33	(1.13)	(1.87)	0.95	(0.30)	(0.56)	15.72	(5.00)	(9.76)	53.44%	0.49	326
2	3.07	(1.18)	(1.99)	0.92	(0.43)	(0.70)	18.01	(5.38)	(10.13)	43.93%	0.39	217
3	3.30	(1.17)	(1.98)	0.99	(0.51)	(0.83)	17.61	(5.49)	(9.93)	42.21%	0.37	169
4	3.60	(1.18)	(2.00)	0.88	(0.56)	(0.89)	17.92	(5.65)	(9.92)	38.86%	0.33	116
						yearly						
0	0.56	(1.02)	(1.91)	0.65	(0.19)	(0.33)	38.58	(8.60)	(22.78)	60.21%	0.57	53
1	2.02	(0.93)	(2.08)	0.60	(0.24)	(0.45)	39.62	(9.46)	(22.03)	51.78%	0.47	31
						Panel B: yields						
						monthly						
0	0.81	(1.04)	(1.98)	-0.21	(0.83)	(1.49)	10.81	(3.97)	(8.57)	26.78%	0.20	-171
1	1.01	(1.03)	(2.11)	-0.69	(0.74)	(1.28)	10.37	(3.89)	(8.82)	29.39%	0.23	-552
2	0.88	(0.91)	(2.15)	-1.21	(0.56)	(1.34)	8.46	(3.74)	(9.45)	39.24%	0.34	-849
3	0.88	(0.90)	(2.17)	-1.36	(0.60)	(1.46)	8.76	(3.64)	(9.35)	40.67%	0.35	-786
4	0.81	(0.87)	(2.17)	-1.55	(0.58)	(1.55)	8.75	(3.49)	(9.27)	44.55%	0.40	-752
5	0.56	(0.85)	(2.12)	-1.70	(0.57)	(1.64)	8.45	(3.41)	(9.29)	47.42%	0.43	-700
6	0.48	(0.84)	(2.11)	-1.87	(0.61)	(1.74)	8.33	(3.38)	(9.23)	48.61%	0.44	-672
7	0.40	(0.85)	(2.10)	-2.01	(0.65)	(1.86)	8.53	(3.36)	(9.13)	48.71%	0.44	-635
8	0.40	(0.86)	(2.11)	-2.12	(0.74)	(2.03)	8.73	(3.42)	(9.07)	46.68%	0.42	-592
9	0.38	(0.88)	(2.11)	-2.20	(0.81)	(2.17)	9.02	(3.45)	(8.99)	45.03%	0.40	-546
10	0.31	(0.89)	(2.10)	-2.26	(0.85)	(2.29)	9.23	(3.46)	(8.94)	44.39%	0.39	-501
11	0.36	(0.90)	(2.11)	-2.25	(0.91)	(2.43)	9.52	(3.51)	(8.89)	42.42%	0.37	-448
12	0.38	(0.90)	(2.11)	-2.28	(0.95)	(2.54)	9.76	(3.51)	(8.85)	41.85%	0.37	-410
						quarterly						
0	-0.41	(0.97)	(1.88)	0.38	(0.17)	(0.46)	10.84	(4.29)	(9.10)	46.67%	0.42	214
1	0.59	(1.01)	(2.16)	0.12	(0.27)	(0.65)	14.32	(4.46)	(9.22)	34.65%	0.29	42
2	0.93	(0.96)	(2.28)	-0.15	(0.35)	(0.87)	14.92	(4.38)	(9.68)	34.60%	0.29	-36
3	0.92	(0.94)	(2.28)	-0.20	(0.40)	(1.04)	15.04	(4.39)	(9.72)	34.75%	0.29	-34
4	0.92	(0.91)	(2.30)	-0.35	(0.43)	(1.18)	15.20	(4.35)	(9.83)	35.94%	0.30	-47
						yearly						
0	-0.87	(0.98)	(2.14)	0.26	(0.18)	(0.41)	26.27	(8.30)	(17.45)	36.26%	0.30	22
1	0.05	(0.85)	(2.23)	-0.01	(0.22)	(0.57)	26.72	(8.69)	(17.58)	30.06%	0.24	-1

Table 2.9: **Ultimate risk for investment-based model.**

The table reports the cross-sectional regression estimation results for the investment-based model:

$$E[r_{i,t+1}] = \lambda_0 + \lambda\beta.$$

For the unconditional model (Panel A) the vector β consists of the following two sets of betas:

$$[\beta_{i,nr}; \beta_{i,r}] = \left[\frac{Cov\left[r_{i,t+j}, \Delta i^S_{nr,t+j}\right]}{Var\left[\Delta i^S_{nr,t+j}\right]}; \frac{Cov\left[r_{i,t+j}, \Delta i^S_{r,t+j}\right]}{Var\left[\Delta i^S_{r,t+j}\right]} \right]$$

where $\Delta i^S_{nr,t+j}$ is the growth rate of the non-residential investments, and $\Delta i^S_{r,t+j}$ is the growth rate in the residential investments, computed over S quarters (years). The conditional model (Panel B) contains additionally the conditional beta $\beta_{i,term}$. We use 25 futures contracts with varying sample period (see Table 2.3). For each model we use the historical means of futures returns (top block of each panel), and yield-based expected returns (bottom block of each panel).

S	λ_0	St. err	λ_{nr}	St. err	λ_r	St. err	λ_{term}	St. err	R^2	R^2_{adj}
					Panel A: Unconditional model					
					mean returns					
					quarterly					
0	-0.03	(0.85)	5.26	(1.37)	-4.26	(2.51)			53.48%	0.49
1	-0.72	(0.91)	7.01	(1.83)	-4.06	(2.57)			56.82%	0.53
2	-0.86	(0.92)	8.51	(2.30)	-4.73	(2.62)			58.17%	0.54
3	-1.11	(0.98)	9.90	(2.89)	-5.65	(3.16)			55.32%	0.51
4	-1.44	(1.06)	11.57	(3.62)	-5.96	(3.77)			51.81%	0.47
					yearly					
0	0.95	(1.02)	3.05	(1.56)	-3.31	(2.21)			22.41%	0.15
1	0.00	(1.07)	3.58	(1.95)	-3.14	(2.13)			20.46%	0.13
					yields					
					quarterly					
0	-2.04	(0.57)	3.37	(0.92)	-4.20	(1.68)			57.58%	0.54
1	-2.27	(0.59)	3.71	(1.19)	-5.37	(1.67)			62.85%	0.59
2	-2.26	(0.60)	4.05	(1.50)	-6.16	(1.71)			63.73%	0.60
3	-2.40	(0.64)	4.44	(1.88)	-7.43	(2.06)			61.41%	0.58
4	-2.56	(0.69)	4.83	(2.35)	-8.53	(2.45)			58.86%	0.55
					yearly					
0	-0.78	(0.79)	0.60	(1.21)	-3.81	(1.72)			19.31%	0.12
1	-1.38	(0.76)	0.91	(1.39)	-4.56	(1.52)			30.13%	0.24
					Panel B: Conditional models					
					mean returns					
					quarterly					
0	0.86	(1.43)	4.70	(1.57)	-4.00	(2.56)	5.62	(7.29)	54.76%	0.48
1	0.37	(1.44)	6.26	(1.98)	-3.75	(2.59)	6.63	(6.72)	58.74%	0.53
2	0.18	(1.46)	7.60	(2.52)	-4.47	(2.65)	6.10	(6.69)	59.77%	0.54
3	0.14	(1.54)	8.61	(3.13)	-5.34	(3.16)	7.18	(6.81)	57.56%	0.52
4	0.08	(1.63)	9.81	(3.86)	-5.62	(3.74)	8.46	(6.92)	55.02%	0.49
					yearly					
0	2.54	(1.06)	1.13	(1.54)	2.11	(2.77)	44.28	(16.15)	42.87%	0.35
1	2.17	(1.19)	2.08	(1.77)	0.59	(2.26)	38.24	(13.34)	42.83%	0.35
					yields					
					quarterly					
0	-1.76	(0.97)	3.19	(1.06)	-4.12	(1.73)	1.75	(4.93)	57.83%	0.52
1	-1.80	(0.95)	3.39	(1.30)	-5.24	(1.71)	2.82	(4.43)	63.55%	0.58
2	-1.76	(0.97)	3.61	(1.66)	-6.03	(1.74)	2.92	(4.41)	64.47%	0.59
3	-1.72	(1.01)	3.74	(2.06)	-7.27	(2.08)	3.89	(4.47)	62.75%	0.57
4	-1.69	(1.06)	3.82	(2.52)	-8.34	(2.44)	4.85	(4.51)	61.00%	0.55
					yearly					
0	0.14	(0.89)	-0.51	(1.29)	-0.66	(2.32)	25.71	(13.53)	31.15%	0.21
1	-0.42	(0.95)	0.24	(1.41)	-2.89	(1.80)	17.04	(10.62)	37.76%	0.29

Table 2.10: **Ultimate risk for consumption model controlling for changes in production.**

The table reports the cross-sectional regression estimation results for the consumption model controlling for changes in production:

$$E[r_{i,t+1}] = \lambda_0 + \lambda\beta,$$

where the vector β consists of the three betas defined in the following way:

$$\begin{aligned} \beta &= Cov(\mathbf{f}, \mathbf{f}')^{-1} Cov(\mathbf{f}, r_{i,t+j}), \\ \mathbf{f} &= (\Delta c^S_{t+j}, \Delta c^S_{t+j} \Delta i^3_{nr,t+j}, \Delta c^S_{t+j} \Delta i^3_{r,t+j}), \end{aligned}$$

and Δi_{nr} is the three quarter growth rate of the non-residential investments, and Δi_r is the three quarter growth rate in the residential investments. We use 25 futures contracts with varying sample period (see Table 2.3). For each model we use the historical means of futures returns, and yield-based expected returns.

S	λ_0	St. err	λ_c	St. err	$\lambda_{c,nr}$	St. err	$\lambda_{c,r}$	St. err	R^2	R^2_{adj}
					Panel A: mean returns					
					quarterly					
0	-0.38	(0.75)	0.63	(0.22)	0.74	(0.25)	0.69	(0.26)	63.82%	0.59
1	-0.66	(0.72)	0.70	(0.23)	6.39	(1.35)	-1.18	(1.58)	69.92%	0.66
2	-0.58	(0.71)	0.87	(0.29)	10.40	(2.10)	-2.74	(2.33)	70.05%	0.66
3	-0.25	(0.71)	0.93	(0.34)	12.89	(2.60)	-3.18	(2.96)	69.83%	0.66
4	-0.01	(0.73)	0.94	(0.37)	14.70	(3.00)	-4.06	(3.40)	69.37%	0.65
					yearly					
0	-0.84	(1.20)	0.34	(0.26)	0.06	(0.04)	-0.03	(0.04)	29.68%	0.20
1	0.94	(0.91)	0.31	(0.27)	1.72	(1.04)	-2.37	(1.43)	39.30%	0.31
					Panel B: Yields					
					quarterly					
0	-2.25	(0.58)	0.13	(0.17)	0.17	(0.19)	0.12	(0.20)	61.56%	0.56
1	-2.17	(0.57)	0.02	(0.18)	2.64	(1.07)	-4.53	(1.25)	66.95%	0.62
2	-2.18	(0.56)	0.02	(0.23)	4.42	(1.66)	-7.12	(1.84)	66.89%	0.62
3	-2.10	(0.56)	0.00	(0.26)	5.70	(2.04)	-8.77	(2.32)	67.38%	0.63
4	-2.04	(0.57)	-0.05	(0.28)	6.66	(2.33)	-10.10	(2.64)	67.33%	0.63
					yearly					
0	-2.25	(0.88)	0.22	(0.19)	-0.01	(0.03)	-0.03	(0.03)	35.74%	0.27
1	-0.84	(0.78)	-0.10	(0.24)	0.36	(0.89)	-2.67	(1.23)	22.65%	0.12

Table 2.11: **Demand and supply elasticities.**

The table reports the estimation of the constant elasticity functions of demand (D) and supply (S) from the following regressions:

$$\begin{aligned}\Delta logD^S_{i,t} &= \alpha_D + \beta_{D,i}\Delta logP_{i,t} + u_{i,t},\\ \Delta logS^S_{i,t} &= \alpha_S + \beta_{S,i}\Delta logP_{i,t} + \varepsilon_{i,t},\end{aligned}$$

where change in demand and supply is measured over different horizons S: $\Delta logI^S_{i,t} = log(\frac{I_{i,t+1+S}}{I_{i,t}})$ with $I^S_{i,t} = \{D^S_{i,t}, S^S_{i,t}\}$. We use 25 futures contracts with varying sample period (see Table 2.3). The estimates are based on the aggregate values of demand (consumption) and supply (Industrial Production Index). We report the estimates of the slope coefficients and their standard errors.

Panel A: Demand elasticity

futures \S	0	St. err	1	St. err	2	St. err	3	St. err	4	St. err
Wheat	0.09	(0.28)	0.11	(0.47)	0.01	(0.63)	-0.43	(0.78)	-1.10	(0.90)
Corn	0.04	(0.29)	-0.14	(0.48)	-0.13	(0.65)	-0.72	(0.81)	-1.65	(0.94)
Oats	0.33	(0.29)	0.16	(0.48)	0.17	(0.64)	-0.11	(0.80)	-0.54	(0.96)
Soybean	0.18	(0.24)	0.10	(0.40)	0.20	(0.54)	-0.03	(0.68)	-0.57	(0.79)
Soybeans Oil	0.04	(0.25)	-0.14	(0.42)	-0.30	(0.56)	-0.67	(0.69)	-1.19	(0.81)
Soybean meal	0.28	(0.22)	0.25	(0.37)	0.42	(0.50)	0.27	(0.63)	-0.18	(0.73)
Live cattle	0.28	(0.42)	0.58	(0.69)	0.48	(0.92)	0.24	(1.17)	0.48	(1.42)
Feeder cattle	0.54	(0.51)	1.24	(0.83)	1.23	(1.10)	1.78	(1.43)	2.42	(1.72)
Live hog	0.17	(0.21)	0.04	(0.35)	0.05	(0.46)	0.33	(0.57)	0.20	(0.67)
Pork Bellies	0.17	(0.20)	0.21	(0.32)	0.07	(0.43)	0.36	(0.54)	0.23	(0.63)
Crude Oil	0.08	(0.22)	-0.26	(0.35)	-0.15	(0.47)	0.07	(0.60)	-0.42	(0.71)
Heating Oil	0.17	(0.24)	0.07	(0.40)	0.03	(0.52)	0.01	(0.65)	-0.30	(0.77)
Unleaded Gasoline	0.23	(0.22)	-0.02	(0.35)	-0.05	(0.46)	0.12	(0.58)	-0.12	(0.71)
Gold	0.27	(0.39)	-0.40	(0.64)	-1.26	(0.84)	-0.97	(1.07)	-1.47	(1.27)
Silver	0.53	(0.22)	0.32	(0.37)	-0.03	(0.49)	0.05	(0.61)	-0.36	(0.71)
Platinum	0.48	(0.27)	0.27	(0.44)	0.06	(0.58)	0.21	(0.73)	-0.24	(0.87)
Copper	0.51	(0.38)	0.52	(0.61)	0.05	(0.80)	0.13	(1.02)	-0.11	(1.35)
Coffee	-0.01	(0.20)	-0.26	(0.33)	-0.09	(0.43)	-0.20	(0.54)	0.02	(0.64)
Sugar	-0.08	(0.17)	-0.20	(0.28)	-0.37	(0.38)	-0.73	(0.47)	-0.91	(0.56)
Cotton	0.48	(0.25)	0.56	(0.41)	-0.16	(0.55)	-0.45	(0.70)	-0.62	(0.83)
S&P 500	0.71	(0.48)	1.35	(0.78)	1.80	(1.04)	2.11	(1.31)	2.81	(1.53)
Japanese Yen	-0.06	(0.64)	0.50	(1.07)	1.48	(1.41)	1.82	(1.78)	2.42	(2.11)
British Pound	-0.79	(0.63)	-0.43	(1.04)	-1.24	(1.38)	-2.18	(1.73)	-2.40	(2.06)
Candian $	-0.60	(1.45)	-0.08	(2.56)	-1.89	(3.44)	-0.81	(4.36)	0.19	(5.20)
Swiss Frank	-0.19	(0.55)	0.50	(0.92)	-0.18	(1.22)	-0.71	(1.53)	-0.37	(1.81)

Panel B: Supply elasticity

futures \S	0	St. err	1	St. err	2	St. err	3	St. err	4	St. err
Wheat	4.17	(1.42)	5.29	(2.50)	9.19	(3.34)	13.06	(4.04)	14.56	(4.67)
Corn	5.06	(1.43)	7.03	(2.53)	10.53	(3.44)	13.16	(4.21)	12.72	(4.95)
Oats	1.64	(1.53)	3.49	(2.52)	5.80	(3.30)	7.34	(4.07)	5.95	(4.78)
Soybean	4.93	(1.18)	7.32	(2.08)	8.55	(2.87)	10.42	(3.53)	11.69	(4.11)
Soybeans Oil	5.28	(1.22)	8.07	(2.16)	9.54	(2.94)	10.41	(3.65)	9.72	(4.29)
Soybean meal	3.85	(1.11)	5.87	(1.94)	6.95	(2.70)	9.16	(3.29)	11.07	(3.81)
Live cattle	3.85	(2.04)	7.58	(3.47)	9.14	(4.67)	7.99	(5.86)	12.37	(6.90)
Feeder cattle	4.65	(2.45)	9.92	(4.16)	11.86	(5.60)	12.06	(7.12)	20.28	(8.19)
Live hog	1.34	(1.07)	2.04	(1.86)	0.69	(2.52)	1.41	(3.09)	4.28	(3.55)
Pork Bellies	0.25	(1.01)	0.28	(1.75)	-0.48	(2.36)	-0.45	(2.90)	2.36	(3.34)
Crude Oil	4.80	(0.95)	7.83	(1.62)	7.62	(2.30)	8.29	(2.86)	8.40	(3.32)
Heating Oil	4.15	(1.04)	7.03	(1.75)	6.65	(2.44)	6.46	(3.03)	6.08	(3.45)
Unleaded Gasoline	4.61	(1.01)	8.18	(1.68)	7.88	(2.43)	7.81	(3.04)	7.78	(3.54)
Gold	2.86	(1.89)	4.88	(3.25)	7.06	(4.40)	12.64	(5.39)	18.81	(6.18)
Silver	3.59	(1.11)	5.80	(1.93)	8.05	(2.58)	11.54	(3.12)	13.15	(3.64)
Platinum	4.07	(1.39)	6.43	(2.40)	8.82	(3.18)	12.15	(3.80)	13.26	(4.38)
Copper	3.08	(1.91)	8.98	(3.08)	11.34	(4.11)	14.63	(4.98)	12.29	(6.55)
Coffee	1.50	(1.04)	2.48	(1.77)	4.08	(2.32)	4.40	(2.77)	3.14	(3.19)
Sugar	2.10	(0.89)	2.81	(1.48)	2.88	(1.97)	2.86	(2.44)	3.17	(2.84)
Cotton	3.08	(1.33)	6.99	(2.23)	10.51	(2.91)	12.75	(3.54)	15.61	(4.03)
S&P 500	-3.44	(2.33)	0.29	(4.06)	2.76	(5.49)	6.90	(6.69)	10.64	(7.57)
Japanese Yen	1.75	(3.18)	3.34	(5.46)	11.69	(7.23)	16.06	(8.90)	20.49	(10.28)
British Pound	2.43	(3.06)	6.12	(5.27)	9.21	(7.14)	10.65	(8.85)	9.38	(10.43)
Candian $	2.56	(7.08)	7.89	(13.01)	16.24	(17.71)	30.05	(21.72)	46.26	(24.80)
Swiss Frank	-0.91	(2.69)	0.05	(4.67)	3.48	(6.31)	3.78	(7.83)	6.96	(9.11)

Figure 2.1: **The relation between mean returns and mean yields.**
The figure depicts the cross-sectional relation between the annualized average log returns on the nearest-to-maturity futures contracts, and the corresponding annual log yield. The plotted lines represent fitted values from the following cross-sectional regression:

$$\overline{r}_{f,i} = \alpha + \beta \overline{y}_i + u_i.$$

The solid line depicts the results from the regression with an intercept and the starred line the results from the regression without an intercept. Full points represent futures on commodities (20) and open points financial futures (5).

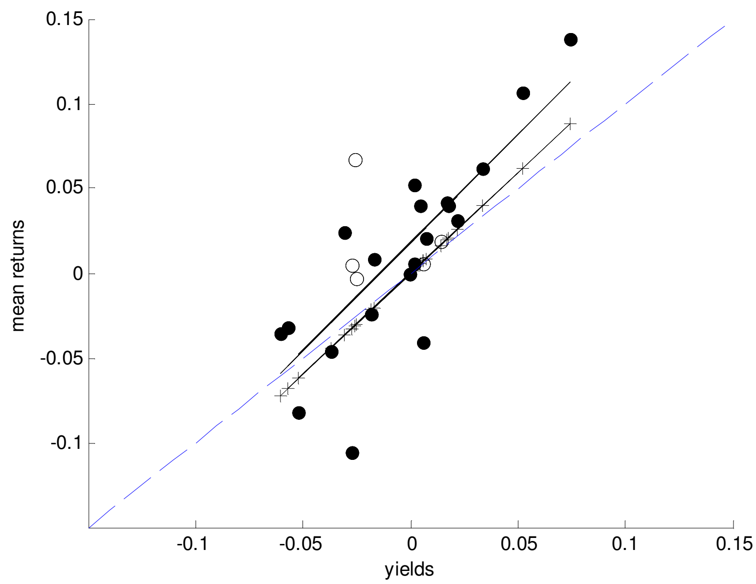


Figure 2.2: **Fitted versus realized returns (quarterly).**
This figure depicts fitted versus realized returns when expected returns are measured with return-based measure (squares) and yield-based measure (triangles). Full points represents commodity futures (20), while open points depict financial futures (5).

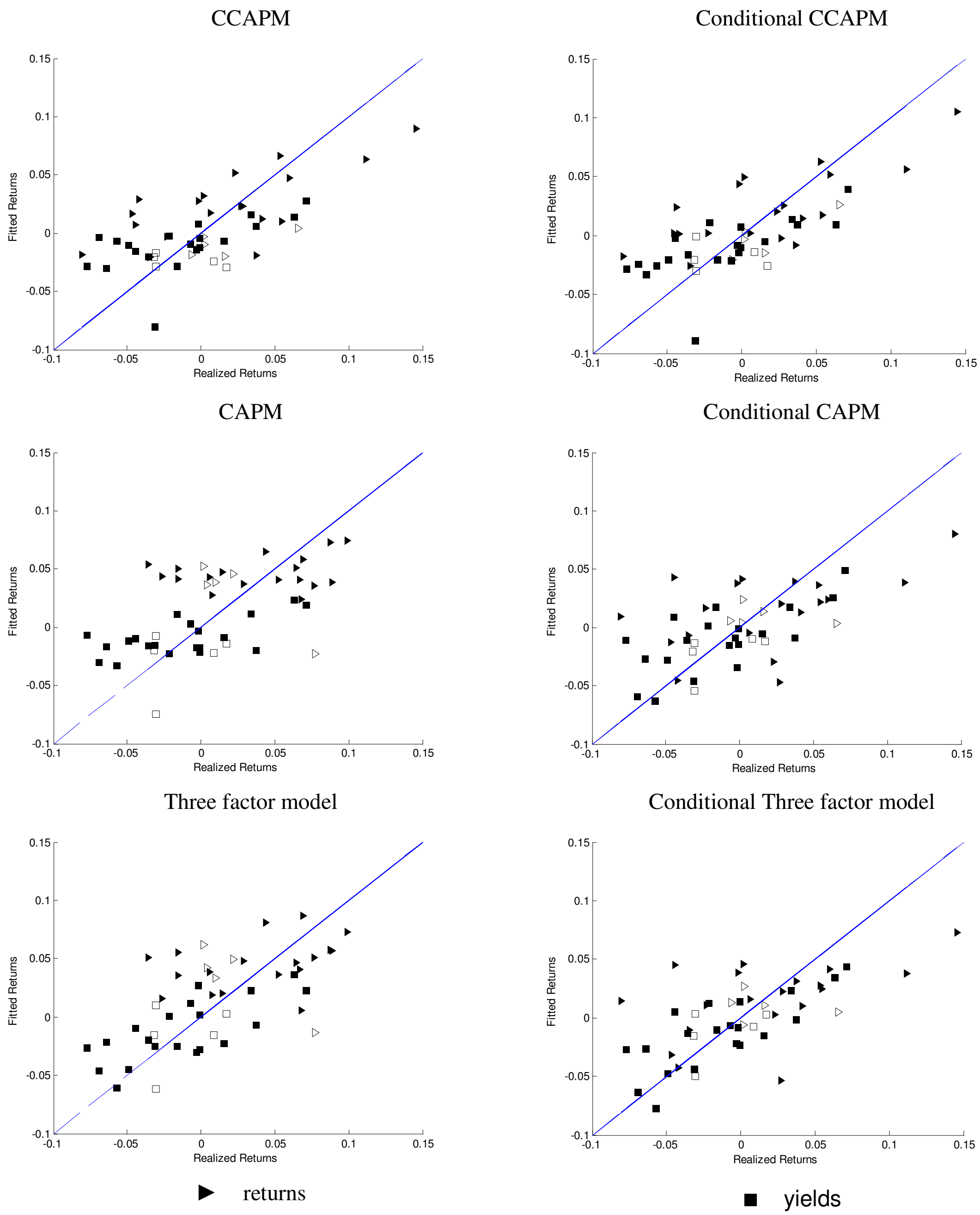
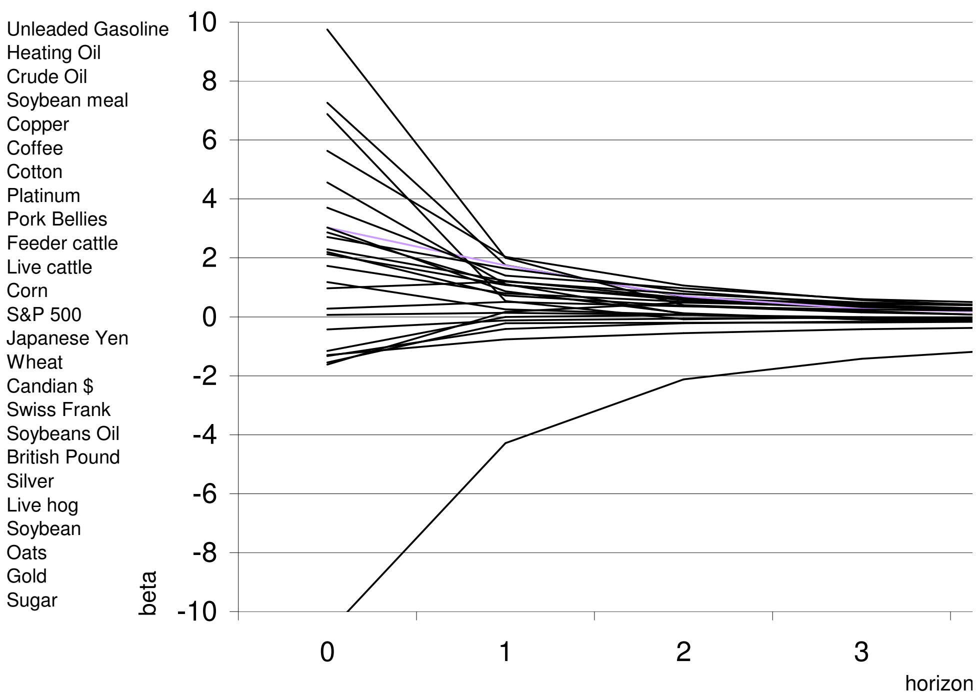


Figure 2.3: **Consumption betas at different horizon.**
The figure depicts consumption betas estimated on 25 futures contracts with varying sample period (see Table 2.3) using the following time-series regression:

$$r_{i,t+1} = \alpha_i + \beta_{i,c_S} \Delta C^S_{t+1} + \epsilon_{i,t+1}$$

based on ultimate consumption risk for different horizons S:

$$\Delta c^S_{t+j} = \log\left(\frac{C_{t+j+S}}{C_t}\right).$$



Chapter 3

An Anatomy of Commodity Futures Returns: Time-varying Risk Premiums and Covariances

3.1 Introduction

Futures contracts are zero cost securities, i.e. they do not require an initial investment, hence the expected futures returns consists of risk premiums only. Understanding these risk premiums is relevant for practitioners, because they affect for instance the hedge decisions of companies, as well as for academics studying them in the context of the asset pricing models. A simple decomposition of futures returns shows that they can be subdivided into the spot and term premiums only. This decomposition is important because the two risk premiums are likely to compensate for different risk factors. For instance, in case of oil futures the spot premium reflects the oil price risk, whereas the term premium mainly reflects the risk that is present in the convenience yield.

Previous literature has identified several variables that have predictive power for futures returns but did not differentiate between the spot and term premiums in futures markets. For instance, Bessembinder and Chan (1992) report that instrumental variables known to possess forecast power in equity and bond markets also possess forecast power for prices in agricultural, metals, and currency futures markets, and Erb and Harvey (2006) show that there is short-term momentum in commodity futures returns. This evidence of predictability is consistent with the existence of time-varying risk premiums in spot and futures markets.

Furthermore, using a simple cost-of-carry relation between the spot and the futures price, the term structure of futures prices depends on the term structure of the cost of carry, or yield.[1] Similarly to the term structure of interest rates, the term structure of yields can be expected to contain term premiums that show up in the expected futures returns, i.e. which may lead to predictable variation in futures returns (de Roon, Nijman, and Veld (1998)). Moreover, Fama (1984) and Fama and French (1987) show that the level of the yield also contains information about the spot-futures premium. This implies that the yield is not only relevant because it gives rise to term premiums, but also because it is linked to the spot-futures premium. Bessembinder et al. (1995) find a negative relation between futures yields and the spot price of the underlying asset, which is indicative of an anticipated mean reversion in asset prices.

Finally, there exists an extensive literature that shows that the net hedge demand for futures contracts induces risk premiums in futures markets. This is known as the hedging pressure effect. Although the description of the hedging pressure effect dates back to Keynes (1930) and Hicks (1939), the empirical relevance of the effect has only been documented during the last two decades. The empirical relevance has been reported in Carter, Rausser, and Schmitz (1983), Chang (1985), Bessembinder (1992), and de Roon, Nijman, and Veld (2000). These studies find that the net position of hedgers in futures indeed results in significant and time-varying risk premiums, an effect that is especially strong in commodity futures markets. It is not clear a priori if net hedge demand has the same influence on term premiums as on spot premiums.

In this chapter we study the time-series properties of futures risk premiums by looking at the spot and term premiums separately. Using a broad cross-section of commodity futures markets and delivery horizons, we show that although average returns in commodity futures markets are claimed to be zero, the spot and term premiums that define them have opposite signs and both premiums are highly predictable. We find that using hedging pressure, past returns and yields we are able to explain up to 30 percent of the time-variation in these risk premiums, with the spot premium being more predictable than the term premiums. This knowledge allows investors to design trading strategies that exploit these different premiums and their predictable variation.

We further investigate this predictability in the context of several asset pricing models. As the price of a futures contract will converge to the spot price of the underlying asset, we can expect that the risk factors that drive the underlying asset returns will also generate risk premiums in the corresponding futures returns. These spot-futures premi-

[1] The yield of a futures contract is defined as the annualized percentage spread between the futures price and the spot price of the underlying asset.

ums have been analyzed for instance by Bessembinder (1992), who investigates whether futures markets and asset markets are integrated and finds that premiums for systematic risk factors in equity markets and 22 different futures markets are very similar. Although Dusak (1973) finds that for three different agricultural contracts the CAPM-beta is basically zero, Carter, Rausser, and Schmitz (1983) find significant market risk for the same futures contracts by allowing for changes in the market risk as a result of changes in the positions of hedgers and speculators. More recently, Erb and Harvey (2006) find that some futures contracts do exhibit systematic risk related to the Fama-French three factors, however, no uniform positive or negative relation can be found across individual contracts. Stronger results are found for systematic risks related to the Consumption CAPM by Jagannathan (1985) who finds market prices of consumption risk for the same aforementioned three futures contracts that coincide with those found in equity markets.

We find that the documented time-variation in expected futures returns or risk premiums seems to be consistent with the consumption-based model but not with the CAPM or the Fama-French model. In other words, predictability documented in futures markets is consistent with the exposure to consumption risk that an investor is undertaking while following a trading strategy that exploits predictability, but not to the market risk or risks related to the Fama-French three factors. As in previous empirical studies the CCAPM does show a high implied risk aversion though. Additionally, since in the consumption-based model the risk of an asset is determined by its covariance with consumption growth, the time-varying expected returns should result from time-varying conditional covariances between futures returns and consumption growth. Indeed, we find that these covariances vary considerably over time. Moreover, for meats and energy futures we find strong evidence of predictability in these conditional covariances. The results for the other futures markets are mixed, suggesting that we either lack an important instrument, or the predictability in futures market varies across markets.

Finally, motivated by Breeden (1980) who argues that consumption betas for commodities may depend on their supply and demand elasticities, we investigate the ability of production growth to forecast expected returns and conditional covariances between futures returns and consumption growth. Consistent with Breeden's argument we find this instrument to have stronger forecasting power for the conditional covariances than for futures returns.

The rest of this chapter is structured as follows. The next section shows a simple decomposition of futures returns, which is followed by a discussion on time-variation in expected returns and covariances. Section 3.3 discusses some estimation issues and

Section 3.4 describes the data. The empirical results are discussed in Section 3.5 and Section 3.6 concludes.

3.2 Theory

3.2.1 A decomposition of futures returns

We start our analysis with a simple decomposition of futures returns that highlights the different premiums that are present in futures markets. Denoting by S_t the spot price of the underlying asset, and by $F_t^{(n)}$ the futures price for delivery at time $t+n$, we use the storage model or cost-of-carry relation to define the *yield*, $y_t^{(n)}$:

$$F_t^{(n)} = S_t \exp\{y_t^{(n)} \times n\}. \tag{3.1}$$

Throughout the chapter we will assume the validity of this cost-of-carry model. Thus, $y_t^{(n)}$ is the per-period yield for maturity n, analogous to the n-period interest rate. It is also the slope of the term structure of (log) futures prices, as is readily seen by solving (3.1) for $y_t^{(n)}$. This yield consists of the n-period interest rate, and possibly other items such as storage costs, and convenience yields depending on the nature of the underlying asset.

From the one-period expected log-spot return we define the spot risk premium $\pi_{s,t}$ as the expected spot return in excess of the one-period yield,

$$\begin{aligned} E_t\left[r_{s,t+1}\right] &= E_t\left[\ln(S_{t+1}) - \ln(S_t)\right] = E_t\left[s_{t+1} - s_t\right] \\ &= y_t^{(1)} + \pi_{s,t}, \end{aligned} \tag{3.2}$$

where we take expectations $E_t[\cdot]$ conditional on the information available at time t and use lower cases to denote log prices. The spot premium $\pi_{s,t}$ can be interpreted as the expected return in excess of the short-term yield, similar to stock returns in excess of the short-term interest rate and dividend yield. It is easy to show that the spot premium is also the expected return of the short-term futures contract, $r_{f,t+1}^{(1)}$, i.e., the return on the futures contract that matures at time $t+1$. This follows from applying the cost-of-carry relation in (3.1) to such a contract and from the fact that the futures price converges to the spot price at the delivery date:

$$\begin{aligned} E_t[r_{f,t+1}^{(1)}] &= E_t[s_{t+1} - f_t^{(1)}] \\ &= E_t[s_{t+1} - s_t - y_t^{(1)}] = \pi_{s,t}. \end{aligned} \tag{3.3}$$

Next, we define a term premium $\pi_{y,t}^{(n)}$ similarly to de Roon, Nijman, and Veld (1998), as the (expected) deviation from the expectations hypothesis of the term structure of yields:

$$ny_t^{(n)} = y_t^{(1)} + (n-1)E_t[y_{t+1}^{(n-1)}] - \pi_{y,t}^{(n)}. \tag{3.4}$$

Without imposing any structure on the term structure of yields, it is important to note that the term premium $\pi_{y,t}^{(n)}$ also shows up in the expected return on a futures contract for delivery at time $t+n$. This follows from the log return on such a contract and applying the cost-of-carry relation again. Using the definitions of $\pi_{s,t}$ and $\pi_{y,t}^{(n)}$ in (3.2) and (3.4) it is easily seen that the expected one-period futures return for a contract that matures at time $t+n$ is:

$$\begin{aligned} E_t[r_{f,t+1}^{(n)}] &= E_t[f_{t+1}^{(n-1)} - f_t^{(n)}] \\ &= \pi_{s,t} + \pi_{y,t}^{(n)} \equiv \pi_{f,t}^{(n)}. \end{aligned} \tag{3.5}$$

Thus, the expected one-period return on an n-period futures contract consists of the futures premium $\pi_{f,t}^{(n)}$ only, which can be separated in a spot premium $\pi_{s,t}$ and a term premium $\pi_{y,t}^{(n)}$. Notice that it follows immediately from (3.3) that $\pi_{y,t}^{(1)} = 0$, i.e., the short term futures contract does not contain a term premium.

This decomposition of the futures premium into a spot premium and a term premium is a useful starting point for our analysis. From (3.3) we have that the spot premium can be identified with a long position in a short-term futures contract. Using spreading strategies it is also possible to isolate the term premium. Combining a long position in an n-period futures contract with a short position in an m-period futures contract on the same underlying asset, the expected return on this portfolio is

$$E_t[r_{f,t+1}^{(n)} - r_{f,t+1}^{(m)}] = \pi_{y,t}^{(n)} - \pi_{y,t}^{(m)}. \tag{3.6}$$

If $m=1$, i.e., if we combine a long position in a long-term contract with a short position in the short-term contract, then the expected return on the spreading strategy is generated by one term premium $\pi_{y,t}^{(n)}$ only. Otherwise the expected return is a combination of two term premiums.

The decomposition in (3.5) is important, because the two risk premiums $\pi_{s,t}$ and $\pi_{y,t}^{(n)}$ are likely to compensate for different risk factors. For instance, in case of oil futures the spot premium, $\pi_{s,t}$, reflects the oil price risk, whereas the term premium, $\pi_{y,t}^{(n)}$, mainly reflects the risk that is present in the convenience yield. Therefore, we will focus on short-term futures trading strategies and on spreading strategies in order to capture the expected returns generated by the different risk factors, i.e., to capture both the spot premiums and the term premiums.

3.2.2 Predictability of futures returns

We analyze predictability[2] in a linear regression framework of futures return $r_{f,t+1}$ for different contracts and different maturities,[3] on a set of forecasting variables $\mathbf{z}_t$:

$$r_{f,t+1} = \beta_0 + \beta_z' \mathbf{z}_t + \varepsilon_{t+1}, \tag{3.7}$$

where β_0 is an intercept, β_z is the $(K \times 1)$ vector of slope coefficients, and ε_{t+1} is orthogonal to the instruments, a mean zero error term. Throughout this chapter we assume that the predictive model in (3.7) is well-specified and that standard regularity conditions hold. Predictability is, then, measured in terms of the vector of slope coefficients β_z, their standard errors and the coefficient of determination R^2.

In order to see if this predictability is consistent with time-varying risk premiums we use the approach of Kirby (1998), who shows how rational asset pricing theory restricts the measures of predictability derived from the linear regression. Previous research shows that the determinants of futures risk premia are usually related to systematic risk based on the CAPM (e.g., Dusak (1973)), the Fama-French model (e.g., Erb and Harvey (2006)), or the Consumption CAPM (e.g., Jagannathan (1985)). The evidence indicates that commodity returns appear to be more strongly related to the changes in aggregate real consumption rather than to the movements in stock markets. Hence, our main interest lies in testing the consistency of the Consumption CAPM and we use the CAPM and the Fama-French three factor models as benchmarks.

Using OLS to estimate (3.7) gives the unrestricted estimate of β_z. Alternatively, we can use the asset pricing model to derive the theoretical value for this coefficient, which gives the restricted estimate of β_z. Let q_{t+1} be a normalized stochastic discount factor (SDF) that has an expectation 1, such that $q_{t+1} = m_{t+1}/E[m_{t+1}]$. As m_{t+1} itself, q_{t+1} assigns a price zero to (excess) returns and to managed (excess) returns $(\mathbf{z}_t r_{f,t+1})$:

$$E\left[q_{t+1} r_{f,t+1}\right] = 0, \tag{3.8}$$

$$E[q_{t+1} r_{f,t+1} \mathbf{z}_t] = 0, \tag{3.9}$$

Starting from these first-order conditions Kirby (1998) obtains restrictions on β_z and R^2

[2] Given the limited number of quarterly observations (see Section 3.4) we focus on the in-sample predictability and refrain from the-out-of sample tests.

[3] We leave out the superscript indicating the maturity of the contract for the simplicity of the exposition.

imposed by any valid asset-pricing model:[4]

$$\begin{aligned}\beta_z &\equiv -\Sigma_{zz}^{-1} Cov(q_{t+1}, r_{f,t+1}(\mathbf{z}_t - \mu_z)), \\ R^2 &\equiv \frac{Cov(q_{t+1}, r_{f,t+1}(\mathbf{z}_t - \mu_z))' \Sigma_{zz}^{-1} Cov(q_{t+1}, r_{f,t+1}(\mathbf{z}_t - \mu_z))}{\sigma_{r_f}^2},\end{aligned} \tag{3.10}$$

where $r_{f,t+1}$ is the futures return, Σ_{zz} is the variance-covariance matrix of instruments $\mathbf{z}_t$, and $\sigma_{r_f}^2$ is the variance of returns.

If predictability observed in the market is consistent with the asset pricing model, then coefficients from predictive regressions should be exactly equal to the values in (3.10), i.e. they should be determined by the covariance of returns with the stochastic discount factor. In other words, predictability observed in the market must be consistent with the exposure to systematic risk that a rational investor is undertaking while following a trading strategy that exploits predictability.

3.2.3 Predictability of covariances

The fact that expected returns are to some extent predictable implies that the conditional expected returns are not constant. If predictability observed in the market is consistent with the asset pricing model, the time-varying expected returns should result from the time-varying conditional covariances between returns and the pricing kernel. Since in the consumption-based asset pricing model the risk of an asset is solely determined by its covariance with consumption growth, we should observe time-varying conditional covariances between returns and consumption growth. If consumption growth and futures returns are jointly log-normally distributed, then

$$E_t\left[r_{f,t+1}\right] + 0.5 Var_t\left(r_{f,t+1}\right) = \gamma Cov_t\left(r_{f,t+1}, \Delta c_{t+1}\right). \tag{3.11}$$

where $\Delta c_{t+1} \equiv \log\left(\frac{C_{t+1}}{C_t}\right)$.

The empirical evidence so far indicates that the conditional covariance between stock returns and consumption is too smooth to match the time-varying expected returns (e.g., Li (2001), Lettau and Ludvison (2001)). However, a recent study by Duffee (2005) shows that the instruments related to the ratio of stock market wealth to consumption are good predictors for the conditional covariances, suggesting that omitting these instruments in earlier studies leads to incorrect conclusions that the conditional covariance is not time-varying.

[4]Details of the derivations can be found in Chapter 4 and in Kirby (1998).

We follow up on this recent finding and focus on the time-variation in the conditional covariances between futures returns and consumption growth. Note that the ratio of the wealth to consumption suggested by Duffee (2005) is not applicable in the futures market as these are zero investment securities. Hence, our aim is to determine whether the conditional covariances for futures markets are predictable using our set of instruments only.

3.3 Estimation issues

We parameterize the consumption-based model using a power utility function with a constant relative risk aversion γ. This implies the following for the stochastic discount factor:

$$m_{t+1} = \delta \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma},$$

where $\left(\frac{C_{t+1}}{C_t} \right)^{-\gamma}$ is the growth in per capita consumption from time t to time $t+1$. We estimate the SDF by imposing the restriction that the risk free rate should be priced correctly and we derive the implied value of the coefficient of risk aversion γ, by fitting the CCAPM to the cross-section of futures returns.

3.3.1 Predictability of futures returns

We test the consistency of the observed predictability with rational asset pricing models using a GMM approach. The vector of moment conditions takes the following form:

$$h(y_{t+1}, \theta) = \begin{bmatrix} m_{t+1} - \mu_m \\ (r_{f,t+1} - \mathbf{x}_t \beta_u)\, \mathbf{x}_t \\ (-r_{f,t+1}\,(m_{t+1} - \mu_m) - \mu_m \mathbf{x}_t \beta_r)\, \mathbf{x}_t \end{bmatrix}, \tag{3.12}$$

where $r_{f,t+1}$ is the futures return, $\mathbf{x}_t = [1, \mathbf{z}_t']$, and $\mathbf{z}_t$ is the $(K \times 1)$ vector of forecasting instruments. The first moment condition identifies the mean of the pricing kernel.[5] The second moment condition identifies all coefficients in the predictive model (3.7) based on the orthogonality condition: $E\left(\varepsilon_{t+1}\mathbf{x}_t\right) = 0$, i.e. the unrestricted estimates of β_z. Finally, the last moment condition identifies the restricted by the pricing kernel estimates of β_z, which follows from the following decomposition of the covariance:

$$E(r_{f,t+1}) = -\frac{Cov(r_{f,t+1}, m_{t+1})}{\mu_m} = -\frac{E(r_{f,t+1}(m_{t+1} - \mu_m))}{\mu_m}. \tag{3.13}$$

[5]These are the moment conditions common for all asset pricing models. The system requires additional moment equations to identify the SDF implied by each of the asset pricing models.

The system in (3.12) is exactly identified, which means that the parameters $\widehat{\beta}_u$ are exactly the same as the OLS estimates from the linear regression of excess returns on forecasting variables. Moreover, we can solve the system explicitly for the estimators by setting $1/T\sum h(y_{t+1},\widehat{\theta}) = \mathbf{0}$:

$$\widehat{\theta} = \begin{bmatrix} \widehat{\mu}_m \\ \widehat{\beta}_u \\ \widehat{\beta}_r \end{bmatrix} = \begin{bmatrix} \frac{1}{T}\sum m_{t+1} \\ (X'X)^{-1} X' r_f \\ -\frac{1}{\widehat{\mu}_m} (X'X)^{-1} X' \left(r_f \left(m_{t+1} - \widehat{\mu}_m\right)\right) \end{bmatrix}.$$

Under standard regularity conditions, the parameter $\widehat{\theta}$ is asymptotically normally distributed as:

$$\sqrt{T}(\widehat{\theta} - \theta) \xrightarrow{d} N\left(0, \left(D'\Omega^{-1}D\right)^{-1}\right),$$

where the matrix D is defined as $D = E\left[\frac{\partial h}{\partial \theta}(y_t, \theta)\right]$ and the matrix Ω is defined as $\Omega = \sum_{j=-\infty}^{\infty} E\left[\mathbf{h}_t \mathbf{h}'_{t-j}\right]$.[6]

We carry out the test of the null hypothesis that $\beta_{u,z} = \beta_{r,z}$, by computing the following Wald test statistic:

$$W = T\left[\widehat{\beta}_{u,z} - \widehat{\beta}_{r,z}\right]' \left[\widehat{\Lambda}\right]^{-1} \left[\widehat{\beta}_{u,z} - \widehat{\beta}_{r,z}\right] \tag{3.14}$$

where $\widehat{\Lambda}$ is the asymptotic covariance matrix of $\left[\widehat{\beta}_{u,z} - \widehat{\beta}_{r,z}\right]$. This covariance matrix is not known but it can be replaced with a consistent estimator without affecting the limiting distribution of the test statistic. It can be calculated as the $(2K \times 2K)$ submatrix of the asymptotic variance-covariance matrix of the GMM estimator $\widehat{\theta}$: $(D'\Omega^{-1}D)^{-1}$. Under the null hypothesis and standard regularity conditions the statistic in (3.14) converges to a χ^2_K distribution, where K is the number of forecasting instruments.

3.3.2 Predictability of covariances

The conditional covariance $\widehat{Cov}_t\left(r_{f,t+1}, \Delta c_{t+1}\right)$ is estimated as the product of the innovations in futures risk premiums and consumption growth projected on the investors' information set. Since we observe neither the true innovations nor the full information set, we use the fitted residuals from the following forecasting regressions as proxies for

[6] Since we expect possible heteroscedasticity among the elements of the disturbance vector $\mathbf{h}_t$ we use the White covariance estimator:

$$\widehat{\Omega} = T^{-1}\sum_{t=1}^{T} \mathbf{h}_t \mathbf{h}'_t.$$

innovations:

$$\begin{aligned} r_{f,t+1} &= \alpha_r' Y_{r,t} + e_{r,t+1}, \\ \Delta c_{t+1} &= \alpha_c' Y_{c,t} + e_{c,t+1} \end{aligned} \tag{3.15}$$

where α_r, and α_c are parameter vectors and the vectors $Y_{r,t}$ and $Y_{c,t}$ are observable at time t and both $e_{r,t+1}$ and $e_{c,t+1}$ are orthogonal to the instruments, mean zero error terms. Then, the conditional covariance is equal to the projection of the product of these residuals $Cov_t^*(r_{f,t+1}, \Delta c_{t+1}) \equiv \widehat{e}_{r,t+1}\widehat{e}_{c,t+1}$ (i.e., an ex post estimate) on a set of instruments $\mathbf{z}_t$:

$$\begin{aligned} Cov_t^*(r_{t+1}, \Delta c_{t+1}) &= \alpha' \mathbf{z}_t + \eta_{t+1}, \\ \widehat{Cov}_t(r_{t+1}, \Delta c_{t+1}) &= \widehat{\alpha}' \mathbf{z}_t, \end{aligned} \tag{3.16}$$

where α is a parameter vector and η_{t+1} is assumed to be orthogonal to the instruments, i.e. the estimation error from estimating the two vectors of residuals in (3.15) is assumed to be unrelated to the instruments $\mathbf{z}_t$. We estimate the conditional covariance using OLS with the White covariance estimator and test whether this conditional covariance is predictable using a Wald test jointly for all slope coefficients. A similar model is used by, e.g., Duffee (2005), and Marquering and Verbeek (2000).

3.4 Data

3.4.1 Futures data

We use quarterly data on 20 commodity futures contracts that are obtained from the Futures Industry Institute (FII) Data Center. The starting date of our sample period varies between contracts, as we use all available information for each futures contract. The earliest starting date is the first quarter of 1968. The end date, the forth quarter of 2004, is common for all series. Hence the number of observations varies between futures contracts in our sample.

The data can be divided into several categories:[7] grains (3), oil and meals (3), meats (4), energy (3), precious metals (4), and food and fiber (3). These markets have relatively large trading volumes and provide a broad cross-section of commodity futures contracts. Details about the delivery months, the exchanges where these futures contracts are traded and the starting dates for each contract are given in Table 3.1.

[7]The classification we use is similar to the one used by the Institute for Financial Markets (IFM).

Following common practice in the literature, futures returns are calculated using a rollover strategy of nearest-to-maturity futures contracts. Until the delivery month, we assume a position in the nearest-to-maturity contract. At the start of the delivery month, the position is changed to the contract with the following delivery month, which then becomes the nearest-to-maturity contract. Prices of futures observed in the delivery month are excluded from the analysis to avoid irregular price behavior that is common during the delivery month. At least four different return series exist for each contract, up till 12 series for the energy contracts. Depending on the delivery dates during the year, the different series are for delivery one to three months apart. We obtain a minimum of 63 and a maximum of 146 observations.

Descriptive statistics are presented in Table 3.2. Panel A describes the returns on the six nearest-to-maturity futures contracts for the six categories of futures contracts. Consistent with previous studies[8] we find that except for the unleaded gasoline and live cattle futures contracts (though not reported here) the estimated unconditional mean returns are statistically indistinguishable from zero at the 5% significance level. The highest average returns - more than 10% on an annual basis - are earned by energy futures, and the negative returns are earned by the grains, food and fiber futures.

3.4.2 Consumption data

We use quarterly, seasonally adjusted, aggregate, real per capita consumption expenditures on nondurable goods and services. The data are retrieved from the National Income and Product Accounts (NIPA) tables in Section 2 on Personal Income and Outlays. The choice of frequency is motivated by the recent research on consumption-based asset pricing (see e.g., Jagannathan and Wang (2005), Parker and Julliard (2005)), which shows that lowering the frequency of consumption growth and returns significantly improves the performance of the CCAPM. The sample period, however, is dictated by the availability of futures prices, as the consumption data are observed at a longer time interval. Panel B of Table 3.2 shows that the log consumption growth during our sample period is slightly above 2% per annum and only moderately volatile.

[8]See, e.g., Bessembinder (1992), Bessembinder and Chan (1992), and de Roon, Nijman, and Veld (2000).

3.4.3 Benchmark factors

The standard benchmark research factors are retrieved from Kenneth French's online data library. As these data are only available on a monthly and an annual basis, we compute quarterly returns by compounding monthly returns. Panel C of Table 3.2 gives the descriptive statistics for the benchmark factors, which confirm their standard features.

3.4.4 Instruments

In this chapter we use three vectors of instruments: $\mathbf{z}_t$ contains instruments that have potential predictive power for futures returns; $Y_{r,t}$ is the vector of instruments used to construct fitted residuals in the equation for futures returns (3.15); and $Y_{c,t}$ is used for fitted consumption growth residuals in the same equation.

At least three variables are known to have predictive power for futures returns: futures yields (e.g., Fama and French (1987)), hedgers' positions (e.g., Bessembinder (1992), de Roon, Nijman, and Veld (2000)), and past returns (e.g., Erb and Harvey (2006)), which constitute our vector of instruments $\mathbf{z}_t$.

Using (3.1), the yield on the n-th nearby futures contract is defined as the spread between the n-th nearby log futures price and the log spot price of the underlying asset, divided by the remaining time to maturity,

$$y_t^{(n)} \equiv \frac{f_t^{(n)} - s_t}{n}, \tag{3.17}$$

Since the moment of settlement within the delivery month is often at the option of one of the contract participants or not easily determined due to market-specific regulations, in most cases we cannot measure the time to maturity of the contract exactly. To solve this problem, we assume that contracts are settled at the 15-th of each delivery month. This assumption may potentially result in some measurement error, in particular for the nearest-to-delivery contracts, since the relative effect of errors will be largest on the shortest maturity, whereas it vanishes for longer-maturity contracts. Since, we are using quarterly data this measurement error is not likely to play a significant role.

Panel D of Table 3.2 shows that yields tend to be larger and more variable for grains futures than for energy futures reflecting the importance of convenience yields and storage costs.

Following previous work, we define the hedging pressure variable in a futures market as the difference between the number of short hedge positions and the number of long hedge positions by large traders, relative to the total number of hedge positions by large traders in that market,

$$q_t = \frac{\#\text{ of short hedge positions} - \#\text{ of long hedge positions}}{\text{total }\#\text{ of hedge positions}}, \tag{3.18}$$

where positions are measured by the number of contracts in the futures market. Hedging pressures are calculated from the data published in the Commitment of Traders reports issued by the Commodity Futures Trading Commission (CFTC). Hedging pressure data are available from the first quarter of 1986, which dictates our sample period. Since net short positions of hedgers create a downward bias in the futures price, this variable is expected to have a positive relation with futures returns.

Panel D of Table 3.2 shows average hedging pressure computed over contracts within our categories of futures (grains, oil and meal, meats, energy, metals, and food and fiber). On average short net positions are held in all six categories of futures contracts but the variability is substantial. If we look at the numbers for each futures contracts (though not reported) we observe both net short and net long mean positions.

Finally, we include past returns in our predictive regressions. We use futures returns from last quarter but we also experiment with further lagged values and the results do not differ from the ones reported here.

In order to estimate the conditional covariances between futures returns and consumption growth, we need estimates of the residuals from forecasting regressions for both futures returns and consumption growth (see Equation (3.15)). For returns we use as instruments a constant and hedging pressure, which form a vector $Y_{r,t}$. For consumption growth residuals we use a constant and consumption growth from preceding periods, which constitutes a vector $Y_{c,t}$.[9]

3.5 Empirical analysis

3.5.1 Risk premiums in futures markets

Consistent with the empirical evidence our 20 futures markets have on average zero returns for all six nearby contracts (see Table 3.2). However, as Bessembinder and Chan (1992) point out, “while zero-mean returns are consistent with the absence of

[9]We follow Duffee (2005) in the choice of instruments. However, we also experiment with larger sets of instruments and we find that the results are not affected by the composition of $Y_{c,t}$, and change only marginally for different $Y_{r,t}$ but remain consistent with the results presented here.

risk premia, they are also consistent with the existence of time-varying risk premia." Hence, the fact that returns are zero on average does not preclude non-zero conditional premiums. In this chapter, in Section 3.2.1, we show that the futures risk premium can be decomposed into two premiums: the spot premium $\pi_{s,t}$ and the term premium $\pi_{y,t}^{(n)}$ for different maturities n. Hence, the zero average return in the futures markets is not only consistent with the pointed out above time-varying risk premiums but also with a situation when the aforementioned spot and term premiums have the opposite sign.

In column 1 of Table 3.3 the unconditional spot premiums $E\left[\pi_{s,t}\right]$ are computed as the average returns on the nearest-to-maturity contracts. The next columns show the average returns on passive spreading strategies, which combine a long position in a longer-maturity contract with a short position in the nearest-to-maturity contract. Using (3.6) and assuming that the term premium on the short contract is approximately zero, the average returns on the spreading strategies give estimates of the unconditional term premiums $E[\pi_{y,t}^{(n)}]$ for various maturities. Significant term premiums are found for many markets, in particular grains, soybeans, meats, unleaded gasoline, silver, and sugar futures. For many futures there is also a clear pattern in the average spreading returns, implying an average term structure of futures prices that is either upward or downward sloping.

The estimated term premiums usually have the opposite signs of the corresponding spot premiums.[10] This may follow from a common risk factor that affects both the spot prices and futures yields for commodity futures. For example, a positive demand shock leads to an immediate increase in the spot prices. However, it will also lead inventories to fall and the convenience yields to rise. Given that we define futures yields as the difference between the interest rate and the convenience yields a positive demand shock decreases futures yields. Hence, a positive shock influences both the spot and term premiums but in the opposite way.

The standard deviations also show a clear structure over the different maturities, where the volatility of the spreading strategies is always increasing in the maturity of the contract. The volatility of the short-term futures contract is always higher than the volatility of the spreading strategies for the same underlying asset, implying that spot price risk is larger than yield or basis risk.

Thus, this section illustrates the relevance of both the spot premiums and term

[10] The results presented in Table 3.3 are based on the sample period that varies across futures (see Table 3.1). Later in the empirical analysis we also use the shorter sample starting from 1986. The results presented here are robust with respect to the sample period chosen.

premiums as components of the average returns on futures contracts. The results show that although returns in commodity futures markets are claimed to be zero the risk premiums that constitute these returns have opposite signs and they can be isolated using simple trading strategies. Next, we analyze the time-variation of these risk premiums.

3.5.2 Predictability of futures returns

We analyze the time-variation in the risk premiums by predicting futures returns using hedging pressure, past returns, and yields induced by the sixth nearby contract. Table 3.4 reports the results from testing the joint significance of slope coefficients from the predictive regressions defined in (3.7) and associated R^2s for both the short term futures returns (spot premiums) and for the spreading returns (term premiums).

It appears that both types of futures returns are predictable using our set of instruments, with the spot returns being more predictable than the spreading returns. This is mostly driven by the hedging pressure variable, which is more strongly related to the spot premiums than to the term premiums. For the nearest-to-maturity contracts we can reject the null hypothesis that all slope coefficients are jointly zero for 13 out of our 20 futures contracts. Not only are the slope coefficients significantly different from zero but more importantly, we are able to explain quite a large fraction of spot return variance reaching a maximum of around 30% for gold. In fact, only two contracts (feeder cattle, and pork bellies) have an R^2 lower than 5%. The least predictable seem to be the longest term premiums (the expected return on a spreading strategy that goes long in the last nearby contracts and short in the nearest-to-maturity contracts). Out of our set of instruments hedging pressure seems to be the strongest instrument for both the spot and the term premiums, however the majority of all individual slope coefficients are significantly different from zero (though not reported here).

We have experimented with a larger set of instruments that includes also the forecasting variables known to predict the excess returns on the stock market. In particular, we use the return on the market index, a dividend yield on the S&P 500 index, a credit risk premium constructed as the difference in yields between Moody's Baa rank bonds and Moody's Aaa rank bonds, and a term structure premium constructed as the difference between 90 days and 30 days Treasury Bill rate. We do not report the results to keep the focus of the chapter.[11] Consistent with Bessembinder and Chan (1992) we find these instruments to be significant only in few futures markets but they do not improve

[11]The results are available from the authors upon request.

significantly the R^2s in our predictive regressions.

This documented predictability will be consistent with rational asset pricing if the unrestricted coefficients (the aforementioned coefficients from the predictive regressions) are equal to the restricted ones described in Section 3.2.2. Rejecting this null hypothesis means that the payoff from the trading strategy, which aims at exploiting predictability, is not consistent with the risk premiums required by rational investors. Table 3.5 reports the results for jointly testing the differences between the unrestricted and the restricted coefficients for the CAPM (Panel A), the Fama-French model (Panel B), and the Consumption CAPM (Panel C). The table reports the Wald test statistics and the associated p-values from testing the null hypothesis jointly for all coefficients together and the ratios of R^2s from the restricted regressions to their unrestricted counterparts reported in Table 3.4.

Looking at the Wald test statistics and their p-values given in Panel A, we are able to reject the null hypothesis at the 10% significance level for the majority of the spot premiums (13 out of 20) and half of the term premiums for the CAPM model. Note that the term premiums exhibit weaker predictability than the spot premiums, which may drive this result. The right block shows the ratio of the restricted R^2s to their unrestricted counterparts, which indicates that the restricted R^2s are almost zero in contrast to the rather high unrestricted ones. Panel B presents the same results for the Fama-French model. The results are similar to the CAPM model but we observe slightly less evidence against the null hypothesis. Also, the restricted R^2s seem to be closer in magnitude to the unrestricted ones but still remain close to zero. In sum, both models seem to be inconsistent with the documented predictability.

The results for the Consumption CAPM (Panel C) show a slightly different pattern: almost all Wald test statistics are rather small and their p-values are far above the 10% significance level. Hence, we do not observe enough evidence against the null hypothesis for all futures except for heating oil, and soybean meal futures. When we compare the restricted R^2s to their unrestricted values, we see that for half of the spot and term premiums they are similar, but for the remaining contracts we observe higher values for the restricted R^2s.[12] Similar values are observed for oil and meals futures while the energy futures yield the most different R^2s. Recall that the estimate of the R^2 is based on the estimates of the slope coefficients, hence the difference between the unrestricted and the restricted R^2 is due to the differences in these estimates. This suggests that when the restricted R^2 differs substantially from the unrestricted one, the restricted

[12]For one contract: unleaded gasoline we even observe restricted R^2s higher than 100%.

model is estimated less precisely, i.e. the point estimates are in fact very different but the high standard errors associated with the restricted coefficients does not allow us to reject the null hypothesis of equality.

It is important to note here that the results depend crucially on the choice of the risk aversion parameter. The results presented in Table 3.4 are based on the implied coefficient of risk aversion from fitting the CCAPM to the cross-section of our futures returns, which results in an estimate of 500.[13] For low risk aversions we are able to reject the null hypothesis for most of the contracts and the restricted R^2s are lower than the unrestricted ones (though they ar higher than the ones obtained for the CAPM and the Fama-French model). This is not a surprising results as the simple CCAPM model is known to be generating high estimates of risk aversion. This result is consistent with numerous theoretical explanations (e.g., heterogenous consumers in Constantinides and Duffie (1996), habit formation in Campbell and Cochrane (1999), or infrequent revision of consumption and investment decisions in Lynch (1996)), which makes the linear relation between expected returns and the covariance with consumption growth hold only approximately resulting in a high implied coefficient of risk aversion. Finding the best performing consumption model is beyond the scope of this chapter, as we are only interested in the ability of consumption growth to predict the time-series of expected returns. Hence, we leave the equity premium puzzle unsolved.

In summary, this section shows that both the spot and the term premiums in futures markets are predictable using hedging pressure, past returns and yields. Moreover, this predictability seems to be consistent with the CCAPM (although for a high risk aversion coefficient) but not with the CAPM and the Fama-French three factor model.The next section focuses on the time-variation in the conditional covariance between the futures returns and consumption growth, hence it sheds more light on the conclusions drawn in this section with respect to the consumption model.

3.5.3 Predictability of covariances

An alternative way of assessing whether the predictability documented in the previous section is consistent with the consumption-based model is to investigate the time-variation of the conditional covariance between the futures returns and consumption growth. In the consumption-based asset pricing model the risk premium of an asset

[13]In a related context of studying the time-variation of the conditional covariances between stock returns and consumption growth Duffee (2005) finds similarly high implied coefficient of risk aversion equal to 160.

is determined by its covariance with consumption growth. Hence if we observe time-varying risk premiums we should observe time-varying conditional covariances between returns and consumption growth.

Figure 3.1 plots the ex post estimates of the conditional covariances, namely the product of fitted residuals from the regressions defined in (3.15). We depict the average values computed within each category of our futures contracts (grains, oil and meal, meats, energy, metals, and food and fiber) and the figure plots these averages for the spot premiums and all the term premiums.

There is considerable time-variation in these ex post covariances for the spot premium and the term premium for longer maturities. The magnitude of this variation is consistent with the results in Duffee (2005) for the stock market. The energy futures exhibit the most volatile series for the spot premiums, although the differences between each ex post estimate of the covariances are not big. In contrast, for the term premiums meats seem to have more volatile ex post covariance than other categories.

Figure 3.2 plots the fitted values from regressing these ex post estimates on our set of instruments as defined in (3.16), which are the average values of the conditional covariances between futures returns and consumption growth. For the spot premiums we see that the conditional covariances in each category vary similarly over time, however, for the term premiums meats still remain the most volatile category.

Table 3.6 gives the results from this projection of the ex post estimates of the covariances on a set of instruments $\mathbf{z}_t$. This set is larger than the one used for predicting futures risk premiums in the previous section. First, motivated by Breeden (1980) who argues that the commodity betas may depend on their supply and demand elasticities, we use production growth as an additional instrument. Moreover, we find this instrument to be more significant in the regressions for the conditional covariances than for the futures returns from the previous section, which is consistent with Breeden's argument formulated for the consumption betas of futures contracts. Second, following Duffee (2005) we add lagged ex post covariance estimates.[14]

The table reports the Wald test statistics and their p-values from testing the joint significance of all slope coefficients together with the R^2s. The results seem to be mixed. There is strong evidence against the null of no predictability for both the spot premiums and term premiums for metal futures. However, we do not have enough evidence against the null for meats and energy, and partially for grains, oil and meals, and food and fiber.

[14] Following Duffee (2005) we use an ex post estimate of the covariance, which is computed as the product of the demeaned futures returns and demeaned consumption growth.

Consistent with this are the results for the R^2s, which are the highest for contracts with slopes jointly significantly different from zero and slightly lower for the remaining contracts. If we look at the individual instruments (though not reported here) we see that out of four instruments we have at least two significant for the majority of the contracts, but the composition varies across futures. This is probably why we do observe quite substantial R^2s even for these futures for which we had jointly insignificant slopes.

The results reported here are weaker than the ones Duffee (2005) finds for the stock market. However, note that the ratio of the stock market wealth to consumption was crucial to finding significant predictability of the conditional covariances.[15] Since this ratio is not applicable in the futures market as these are zero investment securities, it is not surprising that we find weaker evidence of predictability.

In sum, this section shows that the conditional covariances between futures risk premiums and consumption growth vary considerably over time. The set of instruments that we consider is not sufficient to predict these changes in all futures markets, which suggests that either we are lacking an important instrument (in the spirit of Duffee's composition effect) or the conditional covariance in some futures markets is not predictable while it is predictable in the stock market.

3.6 Summary and Conclusions

This chapter analyzes the various risk premiums present in commodity futures markets. A simple decomposition of futures returns shows that futures expected returns consists of two risk premiums only: the spot premium and the term premiums. We show that although average returns in commodity futures markets are claimed to be zero the spot and the term premiums have opposite signs and both premiums are highly predictable.

Using a broad cross-section of commodity futures markets and delivery horizons, we find that both the spot premiums and the term premiums can be predicted using hedging pressure, past returns and yields. We are able to explain up to 30 percent of the time-variation in the risk premiums, with the spot premium being more predictable than the term premium.

We further find that this predictability seems to be consistent with the consumption-based model but not with the CAPM or the Fama-French model. Additionally, we investigate the time-variation in the conditional covariance between futures risk premiums

[15] For example, Li (2001) and Lettau and Ludvison (2001) finds that the conditional covariance between stock returns and consumption is too smooth to match the time-varying expected returns.

and consumption growth. Since in the consumption-based model the risk of an asset is determined by its covariance with consumption growth, the time-varying expected returns should result from the time-varying conditional covariances. Indeed, this is what we find. Moreover, for meats and energy futures we find strong evidence of predictability in these conditional covariances. The results for the other futures markets are mixed, suggesting that we either lack an important instrument, or the predictability in futures market vary across the markets.

Finally, consistent with Breeden's (1980) argument that the consumption betas of commodities may depend on their supply and demand elasticities, we find the production growth to have stronger forecasting power for the conditional covariances than for futures returns.

3.A Figures and Tables

Table 3.1: **Futures contracts.**

The table reports the futures exchange, the delivery months, and the beginning date of the sample period for the 20 commodity futures contracts in our sample. The end date of the sample period, forth quarter of 2004, is common for all contracts.

Futures contract	Exchange	Delivery months	Start date
	Commodities		
Grains			
Wheat	Chicago Board of Trade	3,5,7,9,12	1968 Q4
Corn	Chicago Board of Trade	3,5,7,9,12	1968 Q4
Oats	Chicago Board of Trade	3,5,7,9,12	1974 Q4
Oil & Meal			
Soybean	Chicago Board of Trade	1,3,5,7,8,9,11	1968 Q3
Soybeans Oil	Chicago Board of Trade	1,3,5,7,8,9,10,12	1968 Q3
Soybean meal	Chicago Board of Trade	1,3,5,7,8,9,10,12	1968 Q3
Meats			
Live cattle	Chicago Mercantile Exchange	2,4,6,8,10,12	1976 Q4
Feeder cattle	Chicago Mercantile Exchange	1,3,4,5,8,9,10,11	1977 Q3
Live (lean) hog	Chicago Mercantile Exchange	2,4,6,7,8,10,12	1969 Q4
Pork Bellies	Chicago Mercantile Exchange	2,3,5,7,8	1969 Q2
Energy			
Crude Oil	New York Mercantile Exchange	All	1983 Q4
Heating Oil	New York Mercantile Exchange	All	1979 Q4
Unleaded Gas	New York Mercantile Exchange	All	1985 Q1
Metals			
Gold	Commodity Exchange, Inc.	1,2,4,6,8,10,12	1975 Q1
Silver	Commodity Exchange, Inc.	3,5,7,9,12	1968 Q1
Platinum	New York Mercantile Exchange	1,4,7,10	1972 Q3
Copper	Commodity Exchange, Inc.	1,3,5,7,9,12	1988 Q3
Food/Fiber			
Coffee	New York Board of Trade	3,5,7,9,12	1973 Q4
Sugar	New York Board of Trade	3,5,7,10	1974 Q3
Cotton	New York Board of Trade	3,5,7,10,12	1972 Q4

Table 3.2: **Descriptive statistics.**

The table gives the descriptive statistics for the 20 commodity futures contracts, consumption growth, benchmark factors and instruments. The sample period varies across futures (see Table 3.1). Average returns and standard deviations are annualized and in percentage. Panel A describes the statistics for expected returns on six nearest-to-maturity futures returns. Panels B and C give the same statistics for consumption growth and returns on the benchmark factors respectively. Finally Panel D gives the statistics for hedging pressure and yields computed from the 6th nearby contracts.

	Averages						Standard deviations					
Name	r(1)	r(2)	r(3)	r(4)	r(5)	r(6)	r(1)	r(2)	r(3)	r(4)	r(5)	r(6)
Panel A: expected returns												
Grains	-4.93	-3.98	-2.71	-3.58	-3.29	-1.74	27.2	25.8	23.7	19.3	17.2	15.4
Oil & Meal	2.23	2.93	3.32	3.49	3.52	-0.38	29.71	28.69	27.32	25.56	24.15	19.35
Meats	1.94	2.79	3.64	3.33	3.54	4.73	22.48	20.26	15.44	14.51	14.45	18.82
Energy	10.38	9.20	8.47	8.11	5.87	5.46	34.60	32.12	30.72	29.47	28.85	27.61
Metals	0.26	-1.25	-0.52	-0.94	-0.73	-1.17	24.53	23.69	23.52	23.08	22.55	22.26
Food / Fiber	-3.95	-3.15	-2.79	-2.62	-1.43	-2.39	37.16	34.69	32.77	30.76	26.43	24.68
Panel B: consumption growth												
	Mean	St dev										
Cons growth	2.07	0.8										
Panel C: benchmark factors												
	Mean	St dev										
MKT	5.68	18										
SMB	2.73	12.1										
HML	5.26	12.4										
Panel D: instruments												
	Hedging Pressure			Long-term yield								
	Mean	St dev		Mean	St dev							
Grains	16.90	16.30		5.08	3.19							
Oil & Meal	15.03	18.24		0.17	2.55							
Meats	1.16	26.16		-0.83	2.85							
Energy	5.08	8.14		-4.36	4.39							
Metals	26.92	23.23		0.76	0.92							
Food / Fiber	11.19	18.73		1.72	2.79							

Table 3.3: **The unconditional risk premiums.**

The table gives the unconditional risk premiums for the 20 commodity futures contracts. The sample period varies across futures (see Table 3.1). The short return is defined as the return on the nearest-to-maturity contract. The n-the spreading return is the return on a strategy which takes a long position in the n-th nearby contract and a short position in the nearest-to-maturity contract. Average returns and standard deviations are annualized and in percentage. */** indicates significance level at 10/5 percent.

	Averages						Standard deviations					
	Short return	Spreading returns r(n) - r(1)					Short return	Spreading returns r(n) - r(1)				
Name	r(1)	n=2	n=3	n=4	n=5	n=6	r(1)	n=2	n=3	n=4	n=5	n=6
Wheat	-2.29	0.77	2.98**	3.49**	2.13		25.3	5.1	7.2	9.4	11.3	
Corn	-4.41	0.92	1.60**	3.73**	5.01**	7.46**	25.1	3.7	5.2	7.0	9.2	12.4
Oats	-8.08	1.14	2.07				31.0	7.0	11.4			
Soybean	0.60	1.30**	2.07**	1.51	2.21	3.32**	27.6	4.2	5.1	8.1	9.8	9.5
Soybeans Oil	3.75	-0.30	0.09	0.98	0.96	3.47**	30.7	4.2	6.7	8.0	9.6	10.0
Soybean meal	2.32	1.12	1.11	1.29	0.72	1.45	30.8	6.0	8.9	10.8	12.7	12.7
Live cattle	5.46**	-1.74	-3.04**	-3.37**	-4.06**		14.6	6.0	8.1	9.7	10.3	
Feeder cattle	4.15	0.16	-0.56	-0.56			14.9	3.0	4.1	5.4		
Live hog	2.83	2.43	2.34	1.48	2.50	2.07	26.6	9.3	12.8	16.0	17.8	23.0
Pork Bellies	-4.69	2.82					33.9	10.1				
Crude Oil	11.14	-0.48	-1.14	-1.84	-2.49	-2.97	38.0	5.2	8.1	10.2	12.0	13.7
Heating Oil	5.34	-1.29	-1.26	-1.39	-2.25	-2.36	32.8	5.3	8.0	9.8	11.1	12.0
Unleaded Gas	14.66**	-1.77	-2.39	-2.64			33.0	6.5	9.6	10.8		
Gold	-3.46	-0.08	-0.11	-0.18	-0.28	-0.37	18.9	0.6	1.1	1.6	2.1	2.5
Silver	-4.24	0.17	0.63**	0.32	1.00**	0.36	30.3	1.0	1.8	2.5	3.1	4.1
Platinum	2.79						24.6					
Copper	5.96	-0.06	-0.35	-1.22	-1.17	-1.76	24.3	2.7	4.5	6.3	8.1	10.1
Coffee	0.19	-1.42	-1.68	-1.85	-1.56	2.23	41.5	8.1	11.0	12.7	15.9	14.6
Sugar	-11.85	2.90**	3.75**	3.75			43.7	8.5	12.2	15.3		
Cotton	-0.17	0.91	1.40	2.08	1.69	0.64	26.3	6.4	9.7	11.5	13.5	13.8

Table 3.4: **Predictability in futures risk premiums.**

The table presents the results of fitting a linear regression model in the following form:

$$r_{i,t+1} = \beta_{i0} + \beta_{i1} hp_t + \beta_{i2} mom_t + \beta_{i3} yld_t + \epsilon_{t+1}.$$

The instruments are hedging pressure, past returns and futures yields. The left block reports the Wald test statistics from testing the null hypothesis that all slope coefficients are zero with p-values given in the next block. The right block reports the R^2s. The sample period is from Q1 1988 until Q4 2004.

	Wald test						p-values						R^2					
	Short return	Spreading returns r(n) - r(1)					Short return	Spreading returns r(n) - r(1)					Short return	Spreading returns r(n) - r(1)				
Name	r(1)	n=2	n=3	n=4	n=5	n=6	r(1)	n=2	n=3	n=4	n=5	n=6	r(1)	n=2	n=3	n=4	n=5	n=6
Wheat	7.13	3.48	2.18	2.24	4.00		0.07	0.32	0.54	0.53	0.26		11.36	3.09	2.93	4.88	8.19	
Corn	26.43	0.70	1.86	2.22	3.05	8.49	0.00	0.87	0.60	0.53	0.38	0.04	24.84	0.73	2.62	3.19	5.16	13.40
Oats	13.15	11.18	17.65				0.00	0.01	0.00				11.74	19.55	28.93			
Soybean	4.85	0.77	1.63	8.47	6.94	4.33	0.18	0.86	0.65	0.04	0.07	0.23	10.11	2.16	3.80	8.97	5.66	4.81
Soybeans Oil	7.47	5.03	5.26	4.34	3.89	5.63	0.06	0.17	0.15	0.23	0.27	0.13	9.85	12.42	12.63	9.13	6.86	7.85
Soybean meal	18.29	0.46	0.76	1.90	4.32	7.43	0.00	0.93	0.86	0.59	0.23	0.06	19.16	1.46	3.39	7.64	9.21	9.67
Live cattle	5.16	2.49	1.48	3.02	3.35		0.16	0.48	0.69	0.39	0.34		7.94	5.37	3.62	4.92	7.65	
Feeder cattle	1.52	0.29	1.88	3.76			0.68	0.96	0.60	0.29			2.58	0.53	2.08	5.42		
Live hog	11.52	3.57	6.12	5.94	8.58	7.11	0.01	0.31	0.11	0.11	0.04	0.07	15.58	4.28	7.70	8.98	12.05	12.06
Pork Bellies	3.90	2.83					0.27	0.42					2.84	1.09				
Crude Oil	3.99	2.59	2.43	2.17	1.76	1.49	0.26	0.46	0.49	0.54	0.62	0.69	5.33	3.95	4.04	3.62	2.85	2.32
Heating Oil	5.08	2.42	2.56	2.86	2.82	3.46	0.17	0.49	0.46	0.41	0.42	0.33	9.63	4.24	4.89	4.72	4.47	5.33
Unleaded Gas	10.16	0.72	0.78	1.55			0.02	0.87	0.86	0.67			15.14	1.00	1.12	2.19		
Gold	39.70	17.64	14.79	10.60	11.15	10.62	0.00	0.00	0.00	0.01	0.01	0.01	30.27	20.67	16.76	12.59	12.86	12.79
Silver	10.51	13.52	4.38	11.41	5.14	8.82	0.01	0.00	0.22	0.01	0.16	0.03	9.89	20.82	9.30	16.82	7.06	13.06
Platinum	22.26						0.00						23.84					
Copper	5.33	316.73	5.96	3.48	3.64	4.99	0.15	0.00	0.11	0.32	0.30	0.17	9.10	13.47	8.59	5.44	6.92	12.82
Coffee	7.74	2.03	2.36	2.82	4.00	5.15	0.05	0.57	0.50	0.42	0.26	0.16	14.28	7.21	3.80	4.71	6.38	7.11
Sugar	10.04	43.61	24.40	10.25			0.02	0.00	0.00	0.02			13.73	31.59	25.03	13.21		
Cotton	7.22	1.73	2.89	1.65	0.14	0.44	0.07	0.63	0.41	0.65	0.99	0.93	8.95	3.37	3.69	1.82	0.18	0.59

Table 3.5: **Consistency of documented predictability with asset pricing models.**
The table presents the results of testing the null hypothesis that the difference between the unrestricted and restricted by the asset pricing model coefficients from the following regressions are zero:

$$r_{i,t+1} = \beta_{i0} + \beta_{i1} hp_t + \beta_{i2} mom_t + \beta_{i3} yld_t + \epsilon_{t+1}.$$

The instruments are hedging pressure, past returns and futures yields. The left block reports the Wald test statistics from testing the null hypothesis for all coefficients jointly with p-values given in the next block. The right block reports the ratios of the restricted R^2s to their unrestricted counterparts reported in Table 3.4. The sample period is from Q1 1988 until Q4 2004.

	Wald test						p-values						restricted-R^2 / unrestricted-R^2					
	Short return	Spreading returns r(n) - r(1)					Short return	Spreading returns r(n) - r(1)					Short return	Spreading returns r(n) - r(1)				
Name	r(1)	n=2	n=3	n=4	n=5	n=6	r(1)	n=2	n=3	n=4	n=5	n=6	r(1)	n=2	n=3	n=4	n=5	n=6
							Panel A: CAPM											
Wheat	7.01	3.13	1.68	1.95	3.31		0.07	0.37	0.64	0.58	0.35		0.02	0.02	0.03	0.02	0.02	
Corn	22.96	1.05	1.83	1.73	2.71	7.04	0.00	0.79	0.61	0.63	0.44	0.07	0.00	0.10	0.04	0.03	0.00	0.00
Oats	15.36	11.39	16.56				0.00	0.01	0.00				0.07	0.02	0.03			
Soybean	4.66	1.15	1.60	6.54	5.77	3.87	0.20	0.77	0.66	0.09	0.12	0.28	0.00	0.11	0.01	0.04	0.06	0.05
Soybeans Oil	6.78	3.62	4.82	4.10	4.07	6.02	0.08	0.31	0.19	0.25	0.25	0.11	0.02	0.01	0.02	0.02	0.03	0.03
Soybean meal	19.25	1.38	1.87	2.62	4.47	7.63	0.00	0.71	0.60	0.45	0.22	0.05	0.01	0.41	0.19	0.06	0.06	0.06
Live cattle	4.81	1.99	1.04	1.86	2.70		0.19	0.57	0.79	0.60	0.44		0.02	0.02	0.02	0.05	0.06	
Feeder cattle	0.67	0.38	1.58	2.91			0.88	0.94	0.66	0.41			0.29	0.73	0.14	0.09		
Live hog	11.60	5.21	8.17	7.74	9.60	6.75	0.01	0.16	0.04	0.05	0.02	0.08	0.02	0.32	0.07	0.04	0.04	0.11
Pork Bellies	4.59	3.10					0.20	0.38					0.06	0.02				
Crude Oil	4.99	1.60	1.74	1.79	1.73	1.71	0.17	0.66	0.63	0.62	0.63	0.63	0.22	0.07	0.14	0.24	0.40	0.56
Heating Oil	5.23	3.28	3.63	3.86	3.74	4.39	0.16	0.35	0.30	0.28	0.29	0.22	0.10	0.10	0.09	0.12	0.13	0.14
Unleaded Gas	10.18	0.50	0.87	1.45			0.02	0.92	0.83	0.69			0.05	0.18	0.31	0.17		
Gold	28.98	14.32	13.44	8.79	10.56	9.65	0.00	0.00	0.00	0.03	0.01	0.02	0.01	0.09	0.12	0.16	0.15	0.14
Silver	9.53	12.41	4.92	11.75	5.78	8.80	0.02	0.01	0.18	0.01	0.12	0.03	0.00	0.02	0.00	0.00	0.03	0.01
Platinum	19.34						0.00						0.00					
Copper	5.90	231.42	4.76	2.81	3.12	5.05	0.12	0.00	0.19	0.42	0.37	0.17	0.02	0.02	0.03	0.04	0.02	0.01
Coffee	9.70	2.59	3.67	4.24	6.21	7.53	0.02	0.46	0.30	0.24	0.10	0.06	0.02	0.03	0.06	0.06	0.04	0.02
Sugar	11.21	33.52	21.25	10.25			0.01	0.00	0.00	0.02			0.05	0.02	0.03	0.05		
Cotton	5.93	1.81	3.59	2.15	0.41	0.33	0.11	0.61	0.31	0.54	0.94	0.95	0.01	0.08	0.06	0.10	1.57	0.69

Table 3.5 **continued.**

	Wald test						p-values						restricted-R^2 / unrestricted-R^2					
	Short return	Spreading returns r(n) - r(1)					Short return	Spreading returns r(n) - r(1)					Short return	Spreading returns r(n) - r(1)				
Name	r(1)	n=2	n=3	n=4	n=5	n=6	r(1)	n=2	n=3	n=4	n=5	n=6	r(1)	n=2	n=3	n=4	n=5	n=6
Panel B: Fama-French three factor model																		
Wheat	7.99	4.11	3.00	3.39	5.47		0.05	0.25	0.39	0.34	0.14		0.04	0.13	0.39	0.18	0.13	
Corn	23.71	1.02	2.28	2.33	2.99	7.90	0.00	0.80	0.52	0.51	0.39	0.05	0.01	0.34	0.13	0.04	0.03	0.02
Oats	16.68	10.03	13.79				0.00	0.02	0.00				0.15	0.03	0.03			
Soybean	5.52	1.73	1.37	6.59	5.66	4.05	0.14	0.63	0.71	0.09	0.13	0.26	0.02	0.47	0.22	0.02	0.02	0.01
Soybeans Oil	8.10	3.44	4.60	3.54	4.49	7.09	0.04	0.33	0.20	0.32	0.21	0.07	0.08	0.03	0.03	0.04	0.06	0.06
Soybean meal	19.64	1.49	1.94	2.32	5.42	8.42	0.00	0.68	0.59	0.51	0.14	0.04	0.00	0.37	0.21	0.02	0.01	0.01
Live cattle	4.74	1.72	1.34	1.68	2.37		0.19	0.63	0.72	0.64	0.50		0.12	0.04	0.02	0.10	0.14	
Feeder cattle	1.35	0.55	1.40	1.36			0.72	0.91	0.71	0.71			0.51	2.00	0.19	0.39		
Live hog	13.48	4.03	8.46	8.00	10.06	8.38	0.00	0.26	0.04	0.05	0.02	0.04	0.10	0.18	0.08	0.07	0.09	0.24
Pork Bellies	4.49	3.79					0.21	0.28					0.12	0.17				
Crude Oil	7.52	1.14	1.72	2.04	2.20	2.30	0.06	0.77	0.63	0.56	0.53	0.51	0.69	0.14	0.25	0.44	0.82	1.22
Heating Oil	5.29	2.60	3.14	3.58	3.75	4.53	0.15	0.46	0.37	0.31	0.29	0.21	0.40	0.14	0.12	0.20	0.25	0.28
Unleaded Gas	10.39	1.23	1.72	2.34			0.02	0.74	0.63	0.50			0.19	0.97	0.72	0.41		
Gold	22.86	13.08	11.65	8.25	9.23	8.86	0.00	0.00	0.01	0.04	0.03	0.03	0.06	0.01	0.02	0.02	0.02	0.02
Silver	8.51	13.88	5.36	12.16	7.70	8.67	0.04	0.00	0.15	0.01	0.05	0.03	0.07	0.04	0.01	0.01	0.19	0.01
Platinum	15.27						0.00						0.01					
Copper	3.72	140.37	4.65	2.76	3.10	5.90	0.29	0.00	0.20	0.43	0.38	0.12	0.10	0.06	0.20	0.28	0.17	0.09
Coffee	10.80	2.42	3.17	4.11	6.00	7.64	0.01	0.49	0.37	0.25	0.11	0.05	0.02	0.13	0.41	0.31	0.21	0.16
Sugar	7.11	29.04	18.32	6.81			0.07	0.00	0.00	0.08			0.03	0.05	0.02	0.02		
Cotton	4.69	1.30	2.46	1.52	0.61	0.41	0.20	0.73	0.48	0.68	0.89	0.94	0.01	0.25	0.08	0.18	2.66	0.75
Panel C: Consumption CAPM																		
Wheat	4.92	4.89	4.71	4.62	4.58		0.18	0.18	0.19	0.20	0.21		1.91	14.53	18.78	11.34	3.85	
Corn	6.01	1.79	1.12	1.91	1.79	3.93	0.11	0.62	0.77	0.59	0.62	0.27	0.22	7.27	0.70	0.94	0.37	0.38
Oats	4.37	2.65	3.17				0.22	0.45	0.37				1.50	0.61	0.48			
Soybean	5.17	1.59	0.29	3.83	4.39	3.14	0.16	0.66	0.96	0.28	0.22	0.37	1.67	14.53	1.35	1.33	1.15	0.92
Soybeans Oil	3.07	1.71	0.92	1.07	1.59	1.68	0.38	0.64	0.82	0.79	0.66	0.64	0.57	0.54	0.49	1.02	0.70	0.35
Soybean meal	6.88	1.45	1.62	0.13	2.70	4.35	0.08	0.69	0.65	0.99	0.44	0.23	0.96	9.08	7.21	0.69	0.14	0.21
Live cattle	4.67	3.09	2.44	1.78	1.47		0.20	0.38	0.49	0.62	0.69		2.90	6.72	6.12	3.36	2.26	
Feeder cattle	2.13	1.80	1.29	0.21			0.55	0.61	0.73	0.98			4.00	6.95	0.88	0.45		
Live hog	3.08	2.67	2.60	2.78	3.06	3.09	0.38	0.45	0.46	0.43	0.38	0.38	1.94	2.72	2.18	2.58	3.12	2.78
Pork Bellies	0.79	0.88					0.85	0.83					1.24	1.66				
Crude Oil	2.30	5.43	5.11	3.79	2.78	2.34	0.51	0.14	0.16	0.28	0.43	0.51	8.32	8.71	5.51	4.32	4.05	4.58
Heating Oil	6.45	7.25	6.35	6.40	6.27	6.67	0.09	0.06	0.10	0.09	0.10	0.08	10.17	7.43	10.23	9.15	8.83	7.53
Unleaded Gas	4.73	0.84	1.03	1.55			0.19	0.84	0.79	0.67			7.49	3.42	6.44	5.56		
Gold	2.03	2.31	2.41	2.33	2.36	2.41	0.57	0.51	0.49	0.51	0.50	0.49	0.76	1.19	1.28	1.74	2.09	2.28
Silver	5.63	1.01	0.94	2.11	0.26	2.82	0.13	0.80	0.82	0.55	0.97	0.42	2.54	0.42	1.26	0.02	1.07	0.23
Platinum	1.56						0.67						0.29					
Copper	1.77	5.63	1.30	1.17	1.69	1.67	0.62	0.13	0.73	0.76	0.64	0.64	0.92	0.30	0.18	0.61	0.17	0.09
Coffee	4.02	0.99	1.21	0.96	1.01	0.64	0.26	0.80	0.75	0.81	0.80	0.89	0.65	0.75	2.20	1.84	1.85	1.62
Sugar	1.76	2.77	2.23	2.40			0.62	0.43	0.53	0.49			0.41	0.14	0.03	0.52		
Cotton	3.23	0.92	2.83	3.55	3.25	3.05	0.36	0.82	0.42	0.31	0.35	0.38	3.47	1.58	7.18	16.77	163.55	54.33

Table 3.6: **Predictability in covariances between futures risk premium and consumption growth.**
The table presents the results from projecting the ex post estimate of the covariance between futures returns and consumption growth $Cov_t^*(r_{t+1}, \Delta c_{t+1}) \equiv \widehat{e}_{r,t+1}\widehat{e}_{c,t+1}$ on a set of instruments:

$$Cov_t^*(r_{t+1}, \Delta c_{t+1}) = \alpha_0 + \alpha_1 hp_t + \alpha_2 yld_t + \alpha_3 prod_t + \alpha_4 cov_t + \epsilon_{t+1}.$$

The instruments are hedging pressure, futures yields, production growth and lagged conditional covariance. The left block reports the Wald test statistics from testing the null hypothesis that all slope coefficients are zero with p-values given in the next block. The right block reports the $R^2 s$. The sample period is from Q1 1988 until Q4 2004.

	Wald test						p-values						R^2					
	Short return	Spreading returns r(n) - r(1)					Short return	Spreading returns r(n) - r(1)					Short return	Spreading returns r(n) - r(1)				
Name	r(1)	n=2	n=3	n=4	n=5	n=6	r(1)	n=2	n=3	n=4	n=5	n=6	r(1)	n=2	n=3	n=4	n=5	n=6
Wheat	2.83	6.06	5.14	3.83	2.43		0.59	0.19	0.27	0.43	0.66		5.41	11.72	10.38	8.46	5.65	
Corn	10.91	1.08	2.57	4.45	3.34	5.19	0.03	0.90	0.63	0.35	0.50	0.27	15.15	0.93	3.13	4.15	3.75	7.93
Oats	1.68	6.81	4.91				0.79	0.15	0.30				2.37	9.25	4.43			
Soybean	3.28	13.44	6.54	3.97	4.01	1.54	0.51	0.01	0.16	0.41	0.40	0.82	3.50	26.24	6.29	6.49	4.11	1.18
Soybeans Oil	0.40	4.40	4.33	6.59	4.01	2.01	0.98	0.36	0.36	0.16	0.40	0.73	0.53	6.95	5.38	7.84	4.84	3.56
Soybean meal	10.56	8.53	5.90	3.13	0.81	0.59	0.03	0.07	0.21	0.54	0.94	0.96	6.38	10.16	7.53	2.07	0.63	0.78
Live cattle	2.20	14.36	12.09	7.34	5.64		0.70	0.01	0.02	0.12	0.23		3.88	20.89	22.38	12.95	8.81	
Feeder cattle	2.37	3.47	0.79	1.71			0.67	0.48	0.94	0.79			6.36	6.29	0.48	2.18		
Live hog	6.62	8.49	9.06	12.68	13.25	17.02	0.16	0.08	0.06	0.01	0.01	0.00	14.48	20.70	23.26	27.97	28.21	27.94
Pork Bellies	4.91	8.84					0.30	0.07					9.83	1.38				
Crude Oil	0.73	5.03	4.84	5.43	6.23	5.96	0.95	0.28	0.30	0.25	0.18	0.20	2.51	16.58	15.59	14.32	12.66	11.54
Heating Oil	3.68	3.50	4.69	4.85	5.62	6.67	0.45	0.48	0.32	0.30	0.23	0.15	3.78	7.97	9.27	8.46	8.18	8.64
Unleaded Gas	1.92	1.38	1.95	1.49			0.75	0.85	0.74	0.83			5.04	1.39	1.95	2.02		
Gold	10.76	6.34	5.54	3.27	4.76	4.54	0.03	0.17	0.24	0.51	0.31	0.34	19.21	4.17	3.84	2.51	3.32	3.24
Silver	13.03	2.50	1.90	2.13	1.80	7.94	0.01	0.64	0.75	0.71	0.77	0.09	15.24	3.98	2.08	2.36	5.11	7.61
Platinum	2.73						0.60						4.28					
Copper	10.72	17.54	0.15	0.43	1.47	2.16	0.03	0.00	1.00	0.98	0.83	0.71	11.45	7.91	0.18	0.28	0.74	1.96
Coffee	8.79	3.12	2.89	3.25	3.69	4.27	0.07	0.54	0.58	0.52	0.45	0.37	9.93	5.25	4.61	4.44	5.30	5.90
Sugar	2.49	2.75	2.38	3.15			0.65	0.60	0.67	0.53			2.64	6.61	5.84	5.51		
Cotton	5.83	2.35	6.11	6.19	5.40	6.52	0.21	0.67	0.19	0.19	0.25	0.16	8.24	3.91	10.71	14.53	12.42	13.68

Figure 3.1: **Ex post estimate of the conditional covariance between futures returns and consumption growth.**

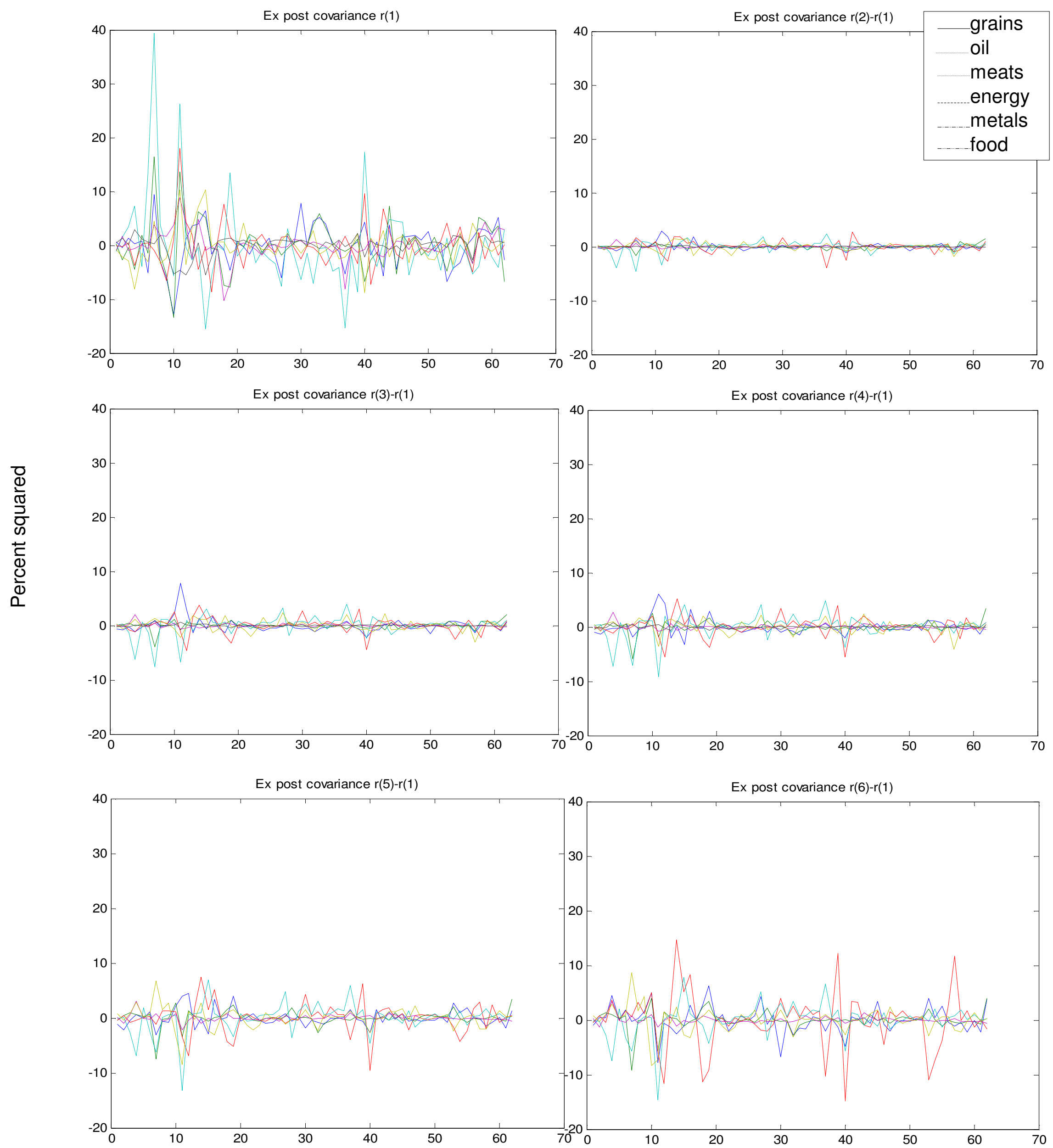
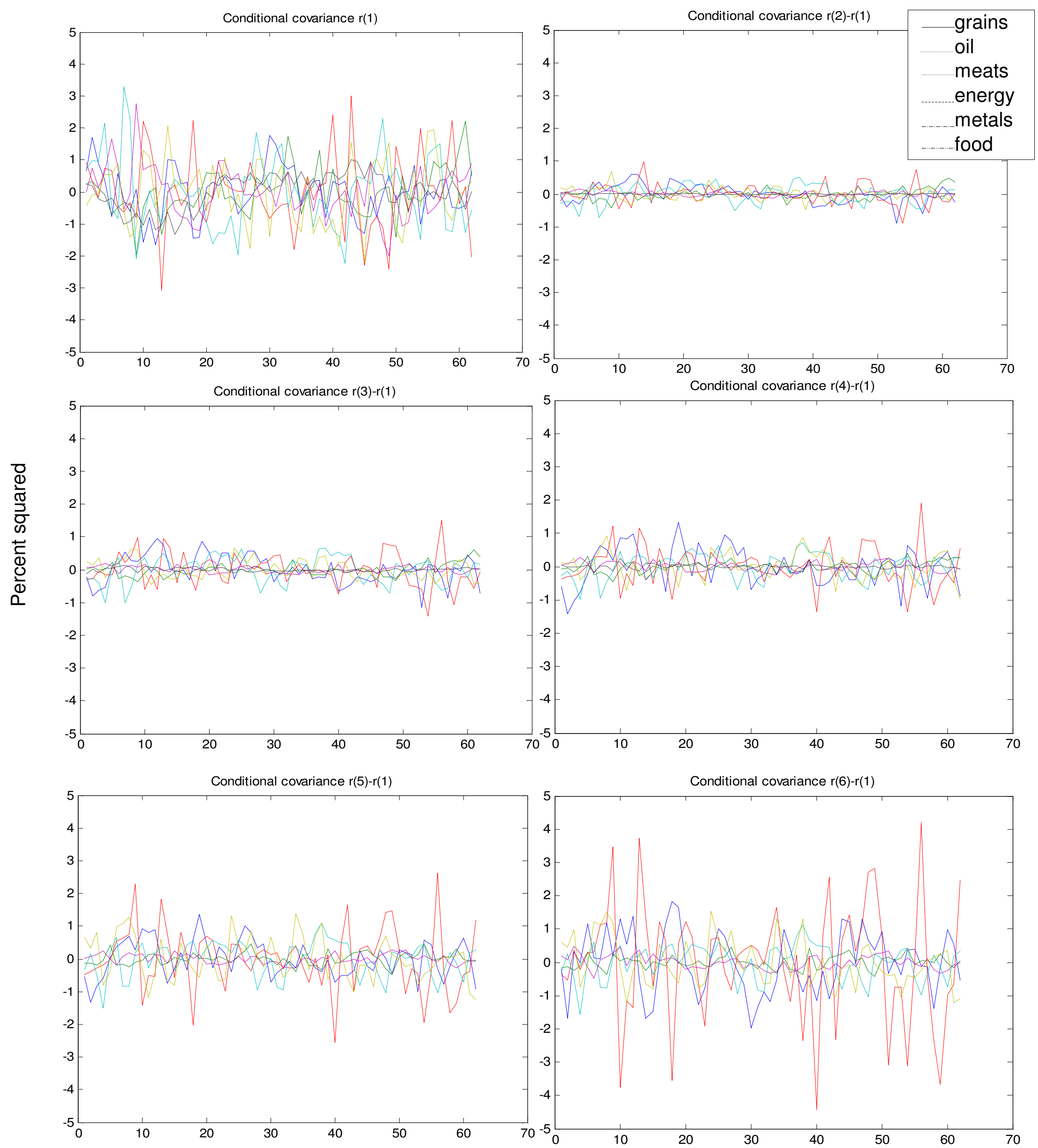


Figure 3.2: **Fitted conditional covariance between futures returns and consumption growth.**



Chapter 4

Predictability in Industry Returns: Frictions Matter

4.1 Introduction

Early studies on industry returns point out that industry factors may play an important role in, for example, predicting risk (Kale, Hakansson, and Platt (1991)) and explaining stock price behavior (Roll (1992)). Boudoukh, Rishardson, and Whitelaw (1994) find a significant cross-sectional relation between industry returns and expected inflation. To the extent that expected inflation is predictable, this finding may shed some light on the predictability of industry returns. Furthermore, industry returns exhibit very strong momentum effects: Moskowitz and Grinblatt (1999) show that industry momentum strategies are even more profitable than individual stock momentum strategies and Pan, Liano, and Huang (2004) add that these industry momentum profits are mainly driven by the own-autocorrelation present in industry portfolios. Finally, Ferson and Korajczyk (1995), and Ferson and Harvey (1991) among others, document direct evidence of predictability among industry portfolios. Moreover, Beller, Kling, and Levinson (1998) find significant predictability for about 80% of value-weighted and 90% of equally-weighted industry returns.

It is well recognized that the ability to predict returns can exist in efficient markets, but what yet remains a puzzle is whether this predictability is an anomaly that could lead markets astray or whether it is simply a feature of financial markets that reflects preferences and expectations. Some academics claim that predictability is a result of time-varying risk premiums present in efficient markets (Bekeart and Hodrick (1992)) or is consistent with rational factor models as it is related to risk factors (Ferson and

Harvey (1991)), while others suggest that this is an evidence of market inefficiency (for example, DeBondt and Thaler (1985) relate predictability to the overreaction of investors). Our main goal is to contribute to this discussion by testing the consistency of observed industry predictability with rational asset pricing models.

Kirby (1998) shows how to assess whether the observed predictability of stock returns documented within a regression framework is consistent with market efficiency. Although he rejects all rational models used in his paper, he concludes that the cross-sectional pattern of predictability appears to be consistent with rationality. His results are derived under the assumptions that investors can trade freely without any costs and constraints, and this may result in the rejection of all the models in his study. It may very well be the case that the profits that are documented in the literature are not attainable for investors simply because the trading rule that led to them is too noisy or there are additional costs and constraints that have been excluded from the analysis.

The aim of this study is to fill this gap. We extend Kirby's approach and analyze whether industry predictability is consistent with rational asset pricing models when market frictions, such as short sales constraints and transaction costs, are taken into account. The inability to go short may force investors to deviate from the trading strategy that aims to exploit predictability in the market, which may lower their profits. The presence of transaction costs may have a similar impact and may also decrease investors' profits, since investors are no longer able to buy and sell the assets at the same price.

Next to the standard statistical approach to hypothesis testing we analyze the consistency of asset pricing models with predictability using a utility-based metric. We assume that returns in the market are predictable and we take the perspective of a mean-variance (MV) investor who either takes into account the restrictions on predictability that follow from an asset pricing model or disregards them completely. We show the economic losses that such an investor encounters while following implications derived from different asset pricing models. Moreover, in situations when statistical tests reject the consistency of asset pricing models we show what is the economic significance of the misspecifications of such models or, put differently, how much a MV investor overstates the gains from predictability that is not consistent with asset pricing. In that respect our study differs from previous work on utility based metrics (e.g., McCulloch and Rossi (1990), Avramov (2004), and Kandel and Stambauch (1996)).

We carry out our empirical investigation on equally-weighted industry returns formed from the stocks listed on the NYSE, AMEX, and NASDAQ stock exchanges, between

February 1965 and December 2002, dividing the universe of stocks in 5 or 10 industry portfolios.

In both specifications, the 5 and 10 industry portfolios, we observe a rather high degree of predictability (i.e., most of the R^2s from the predictive regressions are between 15 and 20 percent). Moreover, statistical tests show that in markets without any trading frictions, asset pricing models are not consistent with this level of predictability. Incorporating trading frictions does improve the performance of the models in terms of generating levels of predictability consistent with those observed in the market. We find that transaction costs, rather than short sales constraints, play a major role, which suggests that strategies that exploit predictability, do not "over-use" short positions. Transaction costs smaller than 50 basis points reconcile the evidence of predictability in most of the cases.

A utility-based metric indicates that a MV investor significantly overstates his utility gain (up to 6 percent per month) from return predictability that is not consistent with asset pricing models. When we incorporate market frictions these gains are substantially reduced. Additionally, we show that without economic evaluation, statistical tests may be inconclusive.

The chapter proceeds as follows. Section 4.2 documents predictability present in our sample. The theory of asset pricing implications on the measures of predictability are given in the following section. Section 4.4 describes the asset pricing models. Section 4.5 addresses some econometric issues. The empirical results are presented in Section 4.6. Finally, Section 4.7 describes the economic significance of our test results and Section 4.8 concludes.

4.2 Predicting industry returns

We analyze the performance of industry returns created from stocks listed on the NYSE, AMEX, and NASDAQ stock exchanges, between February 1965 and December 2002. We use monthly industry returns grouped into 5 and 10 equally-weighted portfolios.[1] A stock is assigned to an industry portfolio at the end of June of year t based on its four-digit SIC code at that time. The data are retrieved from the Kenneth French data library. The definitions of the portfolios are in Table 4.1. Table 4.2 reports the descriptive statistics

[1]We also experiment with the value-weighted portfolios and we find that our conclusions with respect to the rationality of predictability are similar, though we find smaller R^2s. The results are available from the authors upon request.

for our sample, which confirm standard features of industry returns. We observe some degree of heterogeneity in terms of mean returns and standard deviations among industry portfolios. A number of industries show first order autocorrelations exceeding 0.10, but the higher order autocorrelations are almost always close to zero.

We use 5 forecasting variables, which are selected based on findings in previous studies:[2]a dummy for the January effect (Jan); a credit risk premium (Prem) constructed as the difference in yields between Moody's Baa rank bonds and Moody's Aaa rank bonds; a term structure premium (Term) constructed as the difference between 90 days and 30 days Treasury Bill rate; a dividend yield on the S&P 500 index in excess of the risk free rate (Div); and the return on the market index (Mkt). Except for the January dummy all of the forecasting variables are lagged one month. Panel C of Table 4.2 gives the descriptive statistics for the instruments. It appears that our forecasting variables exhibit a high degree of persistence except for the return on the market portfolio, but all autocorrelations decrease in a way that is consistent with stationarity.

4.2.1 Predictability in industry returns

We analyze predictability in a linear regression framework of excess returns $r_{i,t+1}$ on an asset i on a set of forecasting variables $\mathbf{z}_t$:

$$r_{i,t+1} = \beta_{i,0} + \beta'_{i,uz}\mathbf{z}_t + \varepsilon_{i,t+1}, \tag{4.1}$$

where $\beta_{i,0}$ is an intercept, $\beta_{i,uz}$ is a $(K \times 1)$ vector of slope coefficients, and $\varepsilon_{i,t+1}$ a mean zero error term. Predictability is then measured in terms of the vector of coefficients $\beta_{i,uz}$, their standard errors and the coefficient of determination R_i^2.

Table 4.4 gives the results of fitting the above model using our five instruments. As can be seen from the table we are able to explain quite a large fraction of stock return variance. Out of five industry portfolios four have an R^2 between 15% and 17%, while only one industry (utilities) shows weaker predictability with an R^2 equal to almost 5%. Out of 10 industry portfolios three have an R^2 lower than 10% (utilities, telecom, and oil industry) while the rest exhibit a rather high level of predictability, yielding R^2s above 15%. Moreover, the estimated R^2s appear to be stable within our sample period, i.e. for all industries they do not differ substantially when we split the sample into two sub-samples, except for utilities within the 5 industry portfolios, and utilities and telecom

[2]See, e.g., Kirby (1998), Pesaran and Timmermann (1995), Marquering and Verbeek (2000), and Ferson and Harvey (1991).

for the 10 industry grouping.[3]

For both portfolio groupings, the majority of the slope coefficients are significantly different from zero. Moreover, if we test the significance of the coefficients jointly we always reject the null hypothesis for both all industries pooled together and for each industry separately. Thus our industry returns do exhibit patterns of predictability similar to the ones that are documented in previous literature.

4.2.2 Performance of managed industry returns

To asses whether managed industry returns $(\mathbf{z}_t r_{i,t+1})$[4] enhance the investors' opportunity set, i.e., whether investors should enlarge their investment set with managed industry returns created with our 5 instruments, we investigate their relative performance. We first compute the Sharpe ratios associated with each industry (i.e. μ_r/σ_r) and compare it to the maximum Sharpe ratio that can be obtained by forming a portfolio consisting of the managed returns for that industry (i.e. $\left[\mu_{r\otimes z}\Sigma^{-1}_{r\otimes z}\mu_{r\otimes z}\right]^{1/2}$).

Second, we compute, relative to the factor models, the performance of the strategies that invest in industry returns (passive) with the ones that exploit information available at time t (active). For every industry we estimate the following regression:

$$r_{i,t+1} = \alpha_i + \beta_{i,f} f_{t+1} + \epsilon_{t+1}$$

using OLS with the White covariance estimator and test the null hypothesis that the risk adjusted returns, i.e. α_i, are zero. The content of the vector of factors f_{t+1} is dictated by the particular asset pricing model. We use the CAPM and the four factor model in the unconditional and conditional versions.[5] For the passive strategies the test for each industry is based on a univariate regression of $r_{i,t+1}$ on the factors, while for the active strategies, we test the joint significance of intercepts from (K) multivariate regressions of $r_{i,t+1} \otimes \mathbf{z}_t$ on the factors. For both strategies, we also consider the joint test when all industries are pooled together.

Table 4.3 gives the estimated Sharpe ratios and p-values associated with testing the significance of α_i. When we look at the Sharpe ratios (left block of the table) we see a substantial increase when we move from passive strategies to active ones. This holds

[3]These results are available from the authors upon request.

[4]A managed portfolio is one in which allocation between assets is determined according to some signal, in our case a value of an instrument generates such signal (see Cochrane (2001) for details).

[5]The four factor model next to the market factor includes 3 additional factors: the size, the book-to-market and the momentum factors. The details on the specifications of the asset pricing models are postponed to Section 4.4.

for both all industries pooled together and for each industry separately. On average we observe that the Sharpe ratio increases approximately by factor 3.

The mean risk adjusted returns (α_i) to the passive strategies (reported in the middle block of the table) show that these are statistically indistinguishable from zero. For the 5 industry portfolios we only observe few cases when we can reject the null hypothesis, while for the 10 industry portfolios we have slightly more rejections. The majority of the alpha's are positive. This holds for the passive strategies (reported in the table) as well as for the managed returns (though not reported). This indicates that the short positions are not crucial for capturing predictability in our industry returns. When looking at the joint tests it appears that for the 5 industries only the CAPM generates a significant α, while for the 10 portfolios this applies to all models. In general the four factor models perform better than the single factor CAPM, which is in line with previous findings, for example, in Ferson and Korajczyk (1995), and Bekeart and Hodrick (1992). For the active strategies (right block in the table) we observe the opposite pattern. This time we are not able to reject the null hypothesis only in few cases. In the vast majority of the cases the estimated risk-adjusted returns significantly differ from zero.

To test formally whether the active strategies outperform passive ones we run the following regressions:

$$r_{t+1} \otimes \mathbf{z}_t = \gamma_0 + \gamma_1' r_{t+1} + \nu_{t+1}$$

using OLS with the White covariance estimator. If the estimated vector of parameters γ_0 is different from zero it is profitable to extend the industry returns with the managed returns. We test whether the elements of this vector are jointly zero with a standard multivariate Wald test, which has a $\chi^2_{K\times N}$ distribution where K is the number of instruments and N is the number of industries. For the 5 portfolios the statistics is 124.61 ($p < 0.01$) and for the 10 portfolios it takes the value of 263.93 ($p < 0.01$). Thus an investor will benefit from adding managed returns to his investment set.

In summary, this section shows that investors can enhance their investment opportunities by adding managed portfolios to the initial set of industry portfolios. The active industry returns outperform the passive ones since they offer investments opportunities with higher Sharpe ratios and higher risk-adjusted returns ($\alpha's$ relative to the factor models).

4.3 Consistency of predictability with rational theory

4.3.1 Asset pricing implications for the coefficients in predictive regressions

Kirby (1998) shows how rational asset pricing theory restricts the measures of predictability to take on certain values, which allows for testing its consistency. We briefly repeat his derivations.[6] In a standard asset pricing framework,[7] a rational investor maximizes his utility over wealth, which implies the well-known first-order conditions:

$$E_t\left[m_{t+1}R_{i,t+1}\right] = 1, \tag{4.2}$$

where m_{t+1} is an admissible pricing kernel (PK) or stochastic discount factor (SDF), $R_{i,t+1}$ is the gross return on asset i and $E_t[\cdot]$ indicates the expectation conditioned on a full set of information available at time t. The above equality gives conditions for market efficiency, since it states that risk adjusted returns reflect all available information, hence there is no information left in the economy for predictions. Thus, in efficient markets the joint process $(m_{t+1}R_{i,t+1})$, not returns themselves, are not predictable using information known at time t.

Let $r_{i,t+1}$ be the return of asset i in excess of a risk free rate $R_{f,t+1}$, q_{t+1} a normalized pricing kernel that has an expectation 1, i.e. $q_{t+1} = m_{t+1}/E\left[m_{t+1}\right]$. As m_{t+1} itself, q_{t+1} assigns a price zero to excess returns:

$$\begin{aligned} E[q_{t+1}r_{i,t+1}] &= 0, \\ &\Leftrightarrow \; E[r_{i,t+1}] = -Cov\left(q_{t+1}, r_{i,t+1}\right), \end{aligned} \tag{4.3}$$

where the last equation follows from using the definition of covariance. Moreover, q_{t+1} also assigns a price zero to excess returns conditioning on an information set available at time t:

$$E_t[q_{t+1}r_{i,t+1}] = 0, \tag{4.4}$$

which after multiplying with instruments $\mathbf{z}_t$ (which belong to that information set) and by applying the law of iterated expectations leads to the following for the managed

[6] Readers interested in details of the derivations should consult Kirby (1998).

[7] We consider the economy with rational agents and frictionless markets described in Lucas (1978). The same model was used in Kirby (1998) and Hansen and Singleton (1982).

(excess) returns ($\mathbf{z}_t r_{i,t+1}$):

$$\begin{aligned} E[q_{t+1} r_{i,t+1} \mathbf{z}_t] &= 0, \\ &\Leftrightarrow \; Cov(r_{i,t+1}, \mathbf{z}_t) = -Cov\left(q_{t+1}, r_{i,t+1}\mathbf{z}_t\right) - E[r_{i,t+1}]E[\mathbf{z}_t] \end{aligned} \tag{4.5}$$

where the last equation follows from using the definition of covariance twice. After rearranging terms, and substituting (4.3) into (4.5) we get:

$$Cov(r_{i,t+1}, \mathbf{z}_t) = -Cov(q_{t+1}, r_{i,t+1}(\mathbf{z}_t - \mu_z)) \tag{4.6}$$

Finally, using the following definition of the coefficients from linear regressions:

$$\begin{aligned} \beta_{i,uz} &= \Sigma_{zz}^{-1} Cov(r_{i,t+1}, \mathbf{z}_t), \\ R_{i,u}^2 &= \frac{Cov(r_{i,t+1}, \mathbf{z}_t)' \Sigma_{zz}^{-1} Cov(r_{i,t+1}, \mathbf{z}_t)}{\sigma_{r_i}^2}, \end{aligned}$$

we obtain restrictions imposed by a valid asset pricing model:

$$\begin{aligned} &\beta_{i,rz} = -\Sigma_{zz}^{-1} Cov(q_{t+1}, r_{i,t+1}(\mathbf{z}_t - \mu_z)), \\ &R_{i,r}^2 = \frac{Cov(q_{t+1}, r_{i,t+1}(\mathbf{z}_t - \mu_z))' \Sigma_{zz}^{-1} Cov(q_{t+1}, r_{i,t+1}(\mathbf{z}_t - \mu_z))}{\sigma_{r_i}^2}, \end{aligned} \tag{4.7}$$

where Σ_{zz} is the variance-covariance matrix of instruments $\mathbf{z}_t$, and $\sigma_{r_i}^2$ is the variance of returns of asset i.

If predictability observed in the market is consistent with rational asset pricing models, then coefficients from predictive regressions should be exactly equal to the values in (4.7) under the assumption of frictionless markets. In other words, predictability observed in the market must be consistent with the exposure to systematic risk that a rational investor is undertaking while following a trading strategy that exploits predictability. To see this, consider a vector ($\mathbf{z}_t$) in (4.6) with only one instrument. Then, the LHS of (4.6) is the excess payoff of investing ($\mathbf{z}_t - \mu_z$) in an asset (i.e. $E[r_{i,t+1}(\mathbf{z}_t - \mu_z)]$). This is a payoff to a trading strategy that exploits predictability, i.e. portfolio weights are determined based on the information known at time t only. This should be equal to systematic risk or, in other words, the covariance that is priced in the market and constitutes a basis for a risk premium (the RHS of (4.6)).

Note that asset pricing models are rejected, whenever they generate different than observed levels of predictability, either too low ($\beta_{i,uz} \geq \beta_{i,rz}$) or too high ($\beta_{i,uz} \leq \beta_{i,rz}$). These are not, however, symmetric cases. When $(\beta_{i,uz} \geq \beta_{i,rz})$, the actual effect of an instrument in the market is stronger than the model suggests or, put differently, a payoff from a trading strategy that exploits predictability is higher than a rational premium required by the actual risk exposure of such a strategy. Long positions in such assets would take advantage of this additional premium. In the opposite situation, when ($\beta_{i,uz} \leq \beta_{i,rz}$), investors are again not rewarded in a rational way. In this case, however, the asset pricing model overstates the true effect of an instrument hence the compensation received in the market is lower than suggested by a rational asset pricing model. Thus, in this case investors would like to short sell such assets.

4.3.2 Incorporating frictions in the trading process

In the previous section we show the "rational" level of coefficients from predictive regressions when investors can trade freely without any costs and constraints. This, however, seems to be a very strong assumption. For example, the bid-ask spread on the New York Stock Exchange (NYSE) in the period 1965-1990 was estimated to be at least one eight of a dollar, as reported in Luttmer (1996). Yet, these are not the only costs that investors are facing, just to name few: brokerage fees, commissions, taxes, costs of gathering information, etc. Moreover, investors trading at NYSE cannot short sell any asset unless the last trade of the stock is at zero plus tick (the same or higher price). Hence, in this section we introduce short sales constraints and transaction costs into our economy.

Incorporating these frictions into our analysis changes the restrictions imposed on the coefficients from predictive regressions. To elicit the impact of these frictions on the trading strategies that exploit predictability, we assume that the passive strategies are priced correctly. This means that for every asset and for every analyzed pricing kernel the following holds: $E\left[q_{t+1} r_{i,t+1}\right] = 0$, which constitutes our working hypothesis.[8] We first analyze short sales constraints, then we move to transaction costs.

Short sales constraints

He and Modest (1995) show that the presence of short sales constraints affect the first order conditions of the investors' portfolio problem. For managed (excess) returns we obtain:

$$E\left[q_{t+1} r_{i,t+1} \mathbf{z}_t\right] \leq 0,$$

[8] The results presented in Section 4.2.2 (the middle block of Table 4.3) shows that at the industry level this assumption is supported in the majority of the cases, while there is some evidence against it in the joint tests.

where we assume for the vector of instruments that $\mathbf{z}_t \geq 0$.[9]

By subtracting from both sides terms necessary to obtain on the LHS a covariance between the pricing kernel and managed returns, we get the following relations:

$$\begin{aligned} &Cov\left(q_{t+1}, r_{i,t+1}\left(\mathbf{z}_t - \mu_z\right)\right) \leq -E\left[q_{t+1} r_{i,t+1}\right] \mu_z - E\left[r_{i,t+1}\left(\mathbf{z}_t - \mu_z\right)\right], \\ &Cov\left(r_{i,t+1}, \mathbf{z}_t\right) + Cov\left(q_{t+1}, r_{i,t+1}\left(\mathbf{z}_t - \mu_z\right)\right) \leq -E\left[q_{t+1} r_{i,t+1}\right] \mu_z, \end{aligned}$$

which after pre-multiplying the last inequality with (Σ_{zz}^{-1})[10] yields:

$$\beta_{i,uz} - \beta_{i,rz} \leq -\Sigma_{zz}^{-1} \mu_z' E\left[q_{t+1} r_{i,t+1}\right].$$

Recall that our main interest is in the impact of market frictions on the trading strategies that exploit predictability (managed returns). Thus, as described in the introduction to this section, we assume that $E\left[q_{t+1} r_{i,t+1}\right] = 0$. Substituting this in the above finally gives:

$$\beta_{i,uz} - \beta_{i,rz} \leq 0. \tag{4.8}$$

Incorporating short sales constraints into our analysis weakens the restrictions imposed on regression measures of predictability. From the discussion in Section 4.3.1 we know that when $(\beta_{i,uz} \leq \beta_{i,rz})$ the actual effect of some instruments is weaker in the market than suggested by the model, thus rational investors are willing to short sell these assets. However, being prohibited from doing so, investors might not be able to equate their profits with rational risk premiums. Thus, an asset pricing model with short sales constraints would only be rejected in the opposite situation, when $(\beta_{i,uz} \geq \beta_{i,rz})$, meaning that investors are over-compansated for true risk exposures.

Transaction costs

To analyze the effect of transaction costs we follow Luttmer (1996) and focus on proportional transactions costs of the form:

$$\begin{aligned} \tau^A &= \frac{1-b}{1+a}, \\ \tau^B &= \frac{1+a}{1-b}, \end{aligned}$$

where $a > 0$ and $b > 0$ are the ask and bid spread respectively, defined as a percentage of the stock price. Defined in such a way τ^A and τ^B can be interpreted as round trip costs.

[9] In the empirical analysis we rescale the instruments in such a way that they are indeed always positive.

[10] In order to ensure that $\Sigma_{zz} > 0$ we orthogonalized the instruments, which resulted in the diagonal variance-covariance matrix Σ_{zz} (the details are discussed in Section 4.5).

He and Modest (1995) show that in the presence of transaction costs, the restrictions imposed by a valid pricing kernel q_{t+1} on excess asset returns, changes to:

$$\tau_A \leq E_t\left[q_{t+1} r_{i,t+1}\right] \leq \tau_B. \tag{4.9}$$

The investor is not able to buy and sell the asset at the same price, since each trade occurs at either the bid or the ask price. For the managed portfolios, (4.9) implies that

$$\begin{aligned} \mathbf{z}_t \tau_A &\leq E_t\left[q_{t+1}\left(\mathbf{z}_t r_{i,t+1}\right)\right] \leq \mathbf{z}_t \tau_B, \\ \mu_z \tau_A &\leq E\left[q_{t+1}\left(\mathbf{z}_t r_{i,t+1}\right)\right] \leq \mu_z \tau_B, \end{aligned}$$

where the second inequality follows after taking unconditional expectations and assuming that a vector of instruments $\mathbf{z}_t \geq 0$.

Using these two results, we obtain the restrictions on the vector of slope coefficients from the predictive regressions:

$$-\Sigma_{zz}^{-1} \mu_z \Delta \leq \beta_{i,uz} - \beta_{i,rz} \leq \Sigma_{zz}^{-1} \mu_z \Delta, \tag{4.10}$$

where $\Delta = \tau_B - \tau_A$ and all other parameters were described in previous sections (see Appendix 4.A for details on the derivations).

Equation (4.10) shows that incorporating transaction costs in the tests for predictability, weakens the restrictions derived in frictionless markets. The difference between the restricted and the unrestricted coefficients should now be within a range that is determined by the bid-ask spread parameter and normalization terms. If we normalize the instruments to have mean equal to 1, i.e. if we divide instruments by their own means, we can interpret Σ_{zz}^{-1} as the normalization term that accounts for the variability of the instruments. In this case, the restrictions are in fact imposed on the covariances that underly the betas, which should fall within the range determined solely by the bid-ask spread (this follows from pre-multiplying the restrictions in (4.10) by Σ_{zz}):

$$-\Delta \leq Cov(r_{i,t+1}, \mathbf{z}_t) + Cov(q_{t+1}, r_{i,t+1}(\mathbf{z}_t - \mu_z)) \leq \Delta. \tag{4.11}$$

The higher the transaction costs, the weaker the restrictions imposed on the coefficients of predictability. It can easily be seen that the restrictions derived in Kirby (1998) are nested in the ones derived above, when either transaction costs or the normalization term are zero.

By specifying the restrictions as in (4.10) we are able to test to which extent transaction costs can reconcile the predictability in financial markets, by deriving a threshold value for the transaction costs for which the estimated coefficients will fall within that range. If the level of such a threshold is close to the values of transaction costs observed in the market we can conclude that predictability is consistent with that particular pricing model.

4.4 Asset pricing models

We consider a number of admissible pricing kernels m_{t+1} that are known to be partially successful in previous work. We describe each of these specifications below.

Mean-variance pricing kernel

Given the set of asset returns, we can construct a unique pricing kernel, which is linear in the asset returns (hereafter referred to as mean-variance PK or MV-PK):

$$m_{t+1} = \mathbf{R}'_{t+1}\phi \tag{4.12}$$

where $\mathbf{R}_{t+1}$ is an $(N \times 1)$ vector of gross asset returns (including the risk free asset) and ϕ is a vector of parameters. In order to determine ϕ we use the fact that such a PK prices all assets correctly. This yields the following representation for ϕ :

$$\phi = E(\mathbf{R}'_{t+1}\mathbf{R}_{t+1})^{-1}\iota,$$

where ι is an $(N \times 1)$ vector of ones.[11]

Pricing kernels implied by the unconditional factor models

In general, factor models predict that the expected excess return on an asset is proportional to its beta parameters, which measure a tendency of the asset returns to move together with relevant factors:

$$E\left[r_{i,t+1}\right] = \beta_{i,f} E\left[f_{t+1}\right],$$

where $r_{i,t+1}$ is the return on asset i in excess of the risk free rate $R_{f,t+1}$ and f_{t+1} is the vector of factors. This leads to the pricing kernel linear in the factors in the following way:

$$m_{t+1} = 1 - \delta' f_{t+1} \tag{4.13}$$

where δ is a vector of parameters that is assumed to be constant over time.

[11] Note that the inverse exists if returns are linearly independent, which means that there are no redundant assets in our set of returns $(\mathbf{R}_{t+1})$.

The most commonly used factor model is the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965). In this case the vector f_{t+1} contains only one factor, namely the return on the market portfolio in excess of the risk free rate (MKT).

Apart from this one factor model, we also consider the four factor model introduced by Fama and French (1993) and Carhart (1997). In this case the vector f_{t+1} contains 3 additional factor-mimicking portfolios. The SMB factor, which proxies for the risk related to the size and is constructed as the return on the small caps (stocks below the median market value of equity) in excess of the return on the big caps (stocks above the median market value of equity). The HML factor, which is the excess return of the high minus low book-to-market stocks and proxies for the risk related to the value of the book to market ratio. Finally, the UMD factor, which is the difference between the best performing portfolios and the worst performing portfolio and proxies for the Jegadeesh and Titman (1993) momentum effect.

Pricing kernels implied by the conditional factor models

We also consider the conditional version of the above mentioned factor models, which implies that the δ parameters in (4.13) are allowed to vary over time. This leads to the time varying parameters in the representation of the pricing kernel:

$$m_{t+1} = 1 - \delta_t' f_{t+1}. \tag{4.14}$$

We follow the approach in Cochrane (2001) and condition the model in (4.14) by using scaled factors. This means that we expand the set of factors and consider a factor model with fixed coefficients:

$$\begin{aligned} m_{t+1} &= 1 - \delta \left(f_{t+1} \otimes \mathbf{z}_t \right), \\ \delta &= \left[\left(f_{t+1} \otimes \mathbf{z}_t \right)' \left(f_{t+1} \otimes \mathbf{z}_t \right) \right]^{-1} \left(f_{t+1} \otimes \mathbf{z}_t \right)' \iota, \end{aligned}$$

where $\otimes$ denotes the Kronecker product.

4.5 Econometric issues

4.5.1 GMM setup

This section presents the estimation procedure for the mean-variance PK given in equation (4.12). Whenever it will be necessary to modify the procedure in order to estimate other pricing kernels it will be explicitly mentioned in the sequel. The vector of moment conditions takes the following form:

$$h(y_{i,t+1},\theta_i)=\left[\begin{array}{c} m_{t+1}-\mu_m \\ \mathbf{z}_t-\mu_z \\ \left(r_{i,t+1}-\mathbf{x}_t\beta_{i,u}\right)\mathbf{x}_t \\ \left(-r_{i,t+1}\left(m_{t+1}-\mu_m\right)-\mu_m\mathbf{x}_t\beta_{i,r}\right)\mathbf{x}_t \end{array}\right], \tag{4.15}$$

where $r_{i,t+1}$ is the excess return on asset i, $\mathbf{x}_t=[1,\mathbf{z}_t']$, and $\mathbf{z}_t$ is the $(K\times 1)$ vector of forecasting instruments. The first moment condition identifies the mean of the pricing kernel. The subsequent moment conditions identify the means of the forecasting instruments. The third set of moment conditions identify the unrestricted coefficients in the predictive model (4.1) based on the orthogonality condition: $E\left(\varepsilon_{i,t+1}\mathbf{x}_t\right)=0$. Finally, the last set of moment conditions identify the coefficients restricted by the asset pricing model, which follow from the following decomposition of the covariance:

$$E(r_{i,t+1})=-\frac{Cov(r_{i,t+1},m_{t+1})}{\mu_m}=-\frac{E(r_{i,t+1}(m_{t+1}-\mu_m))}{\mu_m}. \tag{4.16}$$

Since the MV-PK does not contain unknown parameters we have the least number of moment conditions in this case. For the CAPM and the four factor models we need to add conditions which identify the vector of parameters δ in the specification of these pricing kernels. In particular we add to the above system $[f_{t+1}\left(1-\delta f_{t+1}\right)]$ for the unconditional models and $[(f_{t+1}\otimes\mathbf{z}_t)\left(1-\delta\left(f_{t+1}\otimes\mathbf{z}_t\right)\right)]$ for the conditional models.

The system in (4.15) is exactly identified, which means that the parameters $\widehat{\beta}_{i,u}$ are exactly the same as the OLS estimates from the linear regression of excess returns on forecasting variables. Moreover, we can solve the system explicitly for the estimators by setting $1/T\sum h(y_{i,t+1},\widehat{\theta}_i)=\mathbf{0}:$

$$\widehat{\theta}_i=\left[\begin{array}{c} \widehat{\mu}_m \\ \widehat{\mu}_z \\ \widehat{\beta}_{i,u} \\ \widehat{\beta}_{i,r} \end{array}\right]=\left[\begin{array}{c} \frac{1}{T}\sum m_{t+1} \\ \frac{1}{T}\sum \mathbf{z}_t \\ \left(X'X\right)^{-1}X'r_i \\ -\frac{1}{\widehat{\mu}_m}\left(X'X\right)^{-1}X'\left(r_i\left(m_{t+1}-\widehat{\mu}_m\right)\right) \end{array}\right].$$

Under standard regularity conditions, the parameter $\widehat{\theta}$ is asymptotically distributed as:

$$\sqrt{T}(\widehat{\theta}_i-\theta)\xrightarrow{d}N\left(0,\left(D_i'\Omega_i^{-1}D_i\right)^{-1}\right),$$

where the matrix D is defined as $D_i=E\left[\frac{\partial h}{\partial\theta_i}(y_{i,t+1},\theta_i)\right]$ and the matrix Ω is defined as $\Omega_i=\sum_{j=-\infty}^{\infty}E\left[\mathbf{h}_{i,t}\mathbf{h}_{i,t-j}'\right].$

Our empirical analysis is based on two assumptions regarding the instruments. The instruments have to be uncorrelated and they can only take nonnegative values (see

Section 4.3.2). To satisfy the first assumption we orthogonalize the forecasting variables, by regressing them on each other and use residual terms as instruments. This leaves us with the following instruments: a dummy for the January effect (Jan); a residual from projecting credit risk premium (Prem) on a constant and Jan; a residual from projecting term structure variable (Term) on all previous variables (a constant, Jan, Prem); a residual from projecting dividend yield (Div) on all previous variables (a constant, Jan, Prem, Term); and a residual from projecting the return on the market (Mkt) on all previous variables (a constant, Jan, Prem, Term, Div).

In order to ensure the nonnegativity constraint we shift the orthogonalized instruments upward until the minimum value becomes a positive number. This transformation is not restrictive, since it does not affect the R^2s of the regressions nor the differences between slope coefficients, which are our main interests here.

4.5.2 Specification of the tests

Let $\widehat{\lambda}_{i,z} = \left[\widehat{\beta}_{i,uz} - \widehat{\beta}_{i,rz}\right]$ be the difference between the unrestricted and restricted regression estimates respectively and $\widehat{\Lambda}_{i,z}$ its covariance matrix. This covariance matrix is not known but it can be replaced with a consistent estimator without affecting the limiting distribution of the test statistic. It can be calculated as the $(2K \times 2K)$ submatrix of the asymptotic variance-covariance matrix of the GMM estimator $\widehat{\theta} : \left(D_i'\Omega_i^{-1}D_i\right)^{-1}$. In order to do so, we need to estimate matrix Ω first. Since we expect possible heteroscedasticity among the elements of the disturbance vector $\mathbf{h}_{i,t}$ we use the White covariance estimator:

$$\widehat{\Omega}_i = T^{-1}\sum_{t=1}^{T}\mathbf{h}_{i,t}\mathbf{h}_{i,t}'$$

We carry out the following tests:

$$\begin{array}{lll} \text{Frictionless market :} & & \\ H_0 : & [\beta_{i,uz} - \beta_{i,rz}] = 0 & \\ W_i : & T\widehat{\lambda}_{i,z}' \left[\widehat{\Lambda}_{i,z}\right]^{-1} \widehat{\lambda}_{i,z} & \end{array} \tag{4.17}$$

Under the null hypothesis the statistic in (4.17) converges to a χ^2_K distribution, where K is the number of forecasting instruments.

$$\begin{array}{ll} \text{Short sales constraints:} & \\ H_0 : & [\beta_{i,uz} - \beta_{i,rz}] \leq 0 \\ W_i : & \min\limits_{\lambda_{i,z}} \; T\left(\lambda_{i,z} - \widehat{\lambda}_{i,z}\right)\left[\widehat{\Lambda}_{i,z}\right]^{-1}\left(\lambda_{i,z} - \widehat{\lambda}_{i,z}\right)' \\ & \qquad \textit{subject to} : \lambda_{i,z} \leq 0 \end{array} \tag{4.18}$$

Under the null hypothesis the statistic in (4.18) converges to a mixture of χ^2 distributions (Kodde and Palm (1986)) and p-values can be obtained in the simulations.

$$\begin{array}{ll} \text{Transaction costs:} & \\ H_0: & -\widehat{\Sigma}_{zz}^{-1}\widehat{\mu}_z\Delta \leq [\beta_{i,uz} - \beta_{i,rz}] \leq \widehat{\Sigma}_{zz}^{-1}\widehat{\mu}_z\Delta \\ W_i: & \min\limits_{\lambda_{i,z}} T\left(\lambda_{i,z} - \widehat{\lambda}_{i,z}\right)\left[\widehat{\Lambda}_{i,z}\right]^{-1}\left(\lambda_{i,z} - \widehat{\lambda}_{i,z}\right)' \\ & \quad \textit{subject to}: -\widehat{\Sigma}_{zz}^{-1}\widehat{\mu}_z\Delta \leq \lambda_{i,z} \leq \widehat{\Sigma}_{zz}^{-1}\widehat{\mu}_z\Delta \end{array} \tag{4.19}$$

Given that the bounds in the restrictions with transaction costs are dependent, we follow the approach suggested by Wolak (1991). He notices that from an asymptotic point of view for each i at most one of the inequalities is relevant, hence we test only this relevant restriction. This is referred to as a local hypothesis testing. A global interpretation would imply that we underestimate the influence of transaction costs on model mis-specification. Driessen, Melenberg, and Nijman (2005) showed that local testing of our null hypothesis is a special case of the test proposed by Kodde and Palm (1986), thus under the null hypothesis the statistic in (4.19) converges to the mixture of χ^2 distributions and p-values can be obtained in the simulations. In order to account for the estimation errors in $\widehat{\Sigma}_{zz}$ and $\widehat{\mu}_z$ we estimate the above Wald test statistic with an auxiliary parameter (see Appendix 4.B for details).

4.6 Results: statistical significance

4.6.1 Frictionless market

The null hypothesis from the tests of consistency of predictability with rational asset pricing in the frictionless markets given in (4.17) states that the unrestricted coefficients are equal to the restricted ones. Rejecting this null hypothesis, means that the payoff from the predictive trading strategy is not consistent with the risk premium desired by rational investors. We carry out the comparisons of the unrestricted and restricted estimates below. We start with the unrestricted and restricted R^2s, which are depicted in Figure 4.1.

It can easily be seen from Figure 4.1 that none of the considered models is able to generate R^2s observed in our sample, with the conditional factor models getting closest. The results are consistent over portfolio groupings, i.e., we observe the same pattern for the 5 and 10 industry portfolios.

We test the differences between the unrestricted and the restricted slope coefficients using the Wald tests described in Section 4.5. The results are given in Table 4.5.

It is easily seen from the table that we can reject the null hypothesis for all models when we look at all portfolios simultaneously. These results are confirmed on the individual industry level for all models except for the conditional four factor model. This confirms the findings in Kirby (1998).

In the unconditional version the four factor model seems to perform better than the single factor CAPM, i.e., we always observe lower values of the Wald test statistics for the four factor model. Nevertheless, the magnitude of their decline is not sufficient in order for the four factor model to be consistent with predictability in the market.

Extending the original sample with managed portfolios (i.e., conditional factor models) further decreases the statistics and in case of the four factor model it is sufficient to reconcile the performance of this model with predictability at the industry level. Moreover, it seems that taking into account dynamic portfolio strategies is more important than the inclusion of additional risk factors, as the conditional CAPM outperforms the unconditional four factor model at the industry level. This is consistent with the evidence of strong return predictability among our industry returns.

In summary, this section shows that existing asset pricing models seem not to be consistent with empirical evidence on predictability in the frictionless market. We proceed by relaxing the assumption of frictionless market maintained in this section and incorporate short sales constraints.

4.6.2 Short sales constraints

When we allow for the presence of short sales constraints our null hypothesis changes into a set of inequality constraints (see (4.18)). The predictability observed in the market will be consistent with rational asset pricing models, when the difference between the unrestricted and the restricted coefficients will be negative. In other words, we allow for the possibility that the premium earned on the market is smaller than the risk premium suggested by the asset pricing model, since investors are not able to short sell such undesired assets. The results are given in Table 4.6.

It seems that an inability to go short does not improve upon the consistency of predictability with rational theory. We observe a decline in Wald test statistics in comparison to the frictionless market case, however, we can still reject the null hypothesis for all models except the conditional four factor model in the joint tests. Apparently for the conditional four factor model, the strategy that exploits profits based on the predictability depends heavily on short positions. In other words, investors who believe in the conditional four factor model are no longer able to benefit from predictability if they are prohibited from short selling industries.

For other asset pricing models we still find statistically significant differences between predictability documented in our sample and the one implied by asset pricing models at the industry level and jointly for the whole market. The results on the differences between slope coefficients for each instrument in the frictionless market (though not reported) show that these differences are mostly positive, except for the term structure variable (Term). This means that the payoff of the strategy that tracks predictability is higher than rational models predict. The question that remains is whether this payoff is high enough to cover the transaction costs that we have ignored so far. We next focus on this issue.

4.6.3 Transaction costs

Apart from short sales constraints, investors are also exposed to transaction costs. In this section we are interested in seeing to what extent proportional transaction costs can reconcile the predictability observed in the market. The presence of such costs changes the equilibrium prices of the assets, i.e., investors are no longer able to buy and sell the assets at the same price. In this situation the null hypothesis in our tests of rational predictability changes and we need to investigate whether the difference between the unrestricted and restricted coefficients falls within a bound determined by transaction costs and a normalization term (see (4.19)). The results are given in Table 4.7.

Even with a reasonable level of transaction costs (12.5 basis points) we observe large changes in our tests. We are no longer able to reject the null hypothesis jointly for all industries for the two conditional models and the unconditional four factor model in both the 5 and 10 portfolios groupings. At the industry level, we still reject in a large number of cases for all models except the conditional four factor model. Only for the utility industry we cannot reject the null hypothesis for all asset pricing models in both portfolio groupings.

When we further increase the transaction costs to 50 basis points, the number of rejections of the null hypothesis further decreases. Jointly for all portfolios we can reject it only for the CAPM. Also at the industry level the number of rejections has dramatically decreased. For example in the 10 industry grouping we observe a decrease from seven rejections with low transaction costs to only one rejection with high transaction costs.

Table 4.8 shows the estimated transaction costs (in basis points) that are needed to reconcile the evidence of predictability with asset pricing theory. The tabel gives the lowest values of transaction costs for which we are not able to reject the null hypothesis at the five percent significance level. The first thing to notice is that the level of transaction costs for all models are not particularly high. The highest costs are needed for the CAPM with the maximum amount equal to 82 basis points. The lowest costs are needed for the conditional four factor model. In fact already in frictionless markets this model produces estimates at the industry level that are consistent with the data (thus zero threshold values in the table) and only when looking at all portfolios jointly we are able to reject the null hypothesis. It turns out that 1 basis point of transaction costs is sufficient to equate the premium earned in the market with rational asset pricing premium.

The unconditional four factor model and the conditional version of the CAPM indicate that the premiums earned in the market while implementing a strategy that tracks predictability is higher than the premium based on the true risk exposure of such strategy. The results in Table 4.8 show that these premiums are not high enough to cover transaction costs of order less than 50 basis points for individual industry and for the joint analysis even below 10 basis points.

4.7 Economic significance

The statistical tests discussed in the previous sections are based on a simple decision to either reject or not reject the asset pricing models. However, as pointed out by Hansen and Jagannathan (1997) such a decision can be based on the fact that the model is only an approximation, or the underlying pricing kernel is identified with an error. In this section, we focus on the economic evaluation of the models in question. In particular, we want to know how bad is the model or, put differently, how much do we gain if we avoid statistically rejected models.

4.7.1 Distance measure

The distance measure of Hansen and Jagannathan (1997) allows for assessing how far the considered model is from the valid one. Kirby (1998) shows how to relate this measure to the restrictions on predictability in the frictionless market. We extend this measure to markets with short sales constraints and transaction costs. Since this statistic is independent of the asset pricing models used and the type of market frictions imposed, we are able to make comparisons across different specifications.

In the frictionless market the distance can be measured by:

$$\widehat{d}_i = \left[\widehat{\lambda}'_{i,z}\widehat{G}\widehat{\Sigma}^{-1}_{i,rz}\widehat{G}\widehat{\lambda}_{i,z}\right]^{1/2}, \tag{4.20}$$

where $\widehat{G}$ and $\widehat{\Sigma}_{i,rz}$ are the sample analogues of $G = \Sigma_{zz}$, and $\Sigma_{i,rz} = Var\left[r_{i,t+1}\left(\mathbf{z}_t - \mu_z\right)\right]$ (see Appendix 4.C for details).

When short sales restrictions are imposed we are interested in the smallest distance that is attainable without violating short sales constraints. In such situations the distance measure is obtained as follows:

$$\widehat{d}_i = \min_{\lambda_{i,z}\leq 0}\left[\left(\lambda_{i,z} - \widehat{\lambda}_{i,z}\right)'\widehat{G}\widehat{\Sigma}_{i,rz}^{-1}\widehat{G}\left(\lambda_{i,z} - \widehat{\lambda}_{i,z}\right)\right]^{1/2} \tag{4.21}$$

Finally, the presence of transaction costs influences only the restrictions on the parameters, hence the distance can be computed in the following way:

$$\widehat{d}_i = \min_{-\widehat{\Sigma}_{zz}^{-1}\widehat{\mu}_z\Delta\leq\lambda_{i,z}\leq\widehat{\Sigma}_{zz}^{-1}\widehat{\mu}_z\Delta}\left[\left(\lambda_{i,z} - \widehat{\lambda}_{i,z}\right)'\widehat{G}\widehat{\Sigma}_{i,rz}^{-1}\widehat{G}\left(\lambda_{i,z} - \widehat{\lambda}_{i,z}\right)\right]^{1/2}. \tag{4.22}$$

In this case, however, we ignore the estimation error present in $\widehat{\Sigma}_{zz}$ and $\widehat{\mu}_z$, thus we compute an upper bound on a true distance measure in the presence of transaction costs.

4.7.2 Utility-based metric

To further investigate the consistency of asset pricing theory with the documented predictability, we investigate the investor's expected utility. We focus on an investor with mean-variance (MV) utility function who allocates his funds into a portfolio by maximizing his expected utility function in the form:

$$\begin{aligned} & \max_w \;\; E\left[U\left(E\left(r_p\right), V\left(r_p\right)\right)\right] = \\ = & \max_w \;\; wE\left(r\right) - \frac{\gamma}{2}w'V\left(r\right)w, \end{aligned} \tag{4.23}$$

where γ is the risk aversion coefficient, w are portfolio weights, r is the vector of all asset returns in our sample, r_p is the portfolio return, and $V(\cdot)$ stands for the variance.

We start our comparison in frictionless markets where the optimal portfolio weights are given by $w^* = \gamma^{-1}V\left(r\right)^{-1}E\left(r\right)$. Next, we also incorporate market frictions into the analysis. When we impose short sales constraints we compute weights based on the maximization problem subject to the constraints that $w \geq 0$. Finally, we take into account transaction costs by correcting portfolio returns with the amount of transaction costs that arise due to rebalancing of the portfolios.

To compute the utility gains or losses we use a certainty equivalent return (CER), that is the rate of return such that:

$$E\left[U\left(CER, 0\right)\right] = E\left[U\left\{E\left(r_p^*\right), V\left(r_p^*\right)\right\}\right].$$

We assume that the optimal allocation is based on the information contained in the instruments only (i.e., $U\left\{E\left(r_p^*|\beta_u\right), V\left(r_p^*|\beta_u\right)\right\}$). We are interested in the utility costs that a MV investor needs to bear while deviating from this optimal allocation by following the implications of asset pricing models (i.e., $U\left\{E\left(r_p^*|\beta_r\right), V\left(r_p^*|\beta_r\right)\right\}$). Hence, the allocation based on the implications of the asset pricing models is treated as suboptimal in our framework. We compare the CERs computed in the following ways:

$$\begin{aligned} CER_u &= w_u^* E\left(r|\beta_u\right) - \frac{\gamma}{2} w_u^{*\prime} V\left(r|\beta_u\right) w_u^* \\ CER_r &= w_r^* E\left(r|\beta_u\right) - \frac{\gamma}{2} w_r^{*\prime} V\left(r|\beta_u\right) w_r^* \end{aligned}$$

4.7.3 Results: economic significance

The estimated Hansen-Jagannathan distance measures are depicted in Figure 4.2 and are presented in Panel A of Table 4.9. Several clear patterns emerge from the figure. First, for every asset pricing model and for both portfolio groupings we observe decreasing distance measures if we move from frictionless market to markets with frictions. Second, we also observe decreasing distance measures if we move from simple asset pricing models (such as mean-variance, the CAPM) to the conditional models. This trend is consistent across different portfolio groupings and different types of market frictions imposed. Finally, we observe a substantial decrease in distance measures when we incorporate transaction costs. From the highest value of 0.74 in frictionless markets (a distance measure implied by the CAPM with 10 industry portfolios) to 0.14, the highest value in market with 50 basis points transaction costs (a distance measure implied by the four factor model with 10 industry portfolios). For the 5 industry portfolios the distance decreases from 0.55 to 0.13 for the same models.

In Panels B and C of Table 4.9 we report the differences in certainty equivalent returns: $CER_u - CER_r$, which reflect a utility loss of an investor who is forced to allocate his funds according to a certain asset pricing model (suboptimally), while the optimal allocation is based on pure statistical evidence of predictability. Alternatively, we may want to interpret the results observed in a sample with caution, and assume that the economy is governed by the dynamics described by an asset pricing model. Then, this difference in CERs can be interpreted as the utility gain the investor cannot obtain from predictable returns, because the predictability is inconsistent with asset pricing models (i.e., the actual amount of predictability is only CER_r).

It appears that the monthly utility losses (or unobtainable gains) are more severe when the investor has to decide between 10 portfolios rather than between 5 portfolios.

In general, the differences in CERs decline as we incorporate market frictions, which confirms the findings based on the distance measure.

The differences in CERs based on the in sample evidence of predictability (Panel B) are economically significant. The highest utility costs (unobtainable gains) in frictionless market are associated with the investment based on the CAPM (4.13% per month for the 5 portfolios and 6.64% per month for the 10 portfolios) and the lowest with the conditional four factor model (1.36% and 3.31% respectively). The same pattern can be observed when we incorporate transaction costs, i.e., the conditional four factor model always yields the lowest utility costs (unobtainable gains). The largest decrease in the utility costs (unobtainable gains) are observed for the case where short sales constraints are introduced. This is in contrast with the statistical tests, which showed that in such case asset pricing models are not consistent.

If we look at the differences in CERs based on one-period ahead forecasts (Panel C) the effect of incorporating short sales constraints disappears. In fact, in this case the utility costs (unobtainable gains) increase for all models except for the conditional four factor model. In general, the utility costs (unobtainable gains) are smaler for one-period ahead forecasts (Panel C) than for the in-sample evidence of predictability (Panel B), which further supports the view that investors are not able to benefit from the observed high in-sample predictability. When we incorporate transaction costs, the differences in CER for four factor models, in both the unconditional and conditional version as well as across the portfolio groupings, are virtually zero. This confirms the statistical tests which showed that the benefits from exploiting predictability are consistent with the risk exposures as described by these models.

In frictionless markets the highest utility losses (unobtainable gains) are observed for factor models, with the highest value equal to 0.57% (for the conditional four factor model). This may at first appear to be counterintuitve as one may expect that more sophisticated models should yield lower utility costs. Recall that the difference between the unrestricted and restricted coefficients is not statistically significant at the industry level, but it is significant in the joint tests when we pooled all industries together. Moreover, Avramov (2004) shows that asset pricing models that explain more of the sample evidence on predictability exert stronger influence on asset allocations. Even though the difference between the unrestricted and restricted coefficients is small (or smaller than for the other models), it is apparently sufficient to induce significant differences in the allocation of funds.

Additionally, our results indicate that without economic evaluation, statistical tests on consistency of rational models with observed predictability may be inconclusive. The conditional CAPM with transaction costs equal to 50 basis points, which is statistically consistent with the data, yields economically significant utility costs (unobtainable gains), i.e. an investor faces certainty equivalence loss as high as 5.46% per month. This suggests that even though the differences between the unrestricted coefficients and the coefficients restricted by the asset pricing model are not statistically significant, they are sufficient to induce significant changes in the allocation of funds.

To conclude the results in this section show that trading frictions influence the allocation of funds and decrease investor's utility.

4.8 Conclusions

The main focus of this study is on the consistency of predictability with rational asset pricing theory. In particular, we focus on industry returns mainly because previous literature has pointed out that they posses features, which make them easier to predict. The most important one is the strong momentum effect documented first by Moskowitz and Grinblatt (1999), which is mainly driven by the own-autocorrelation (Pan, Liano, and Huang (2004)). Indeed, our empirical tests confirm this. We found strong return predictability among the 5 and 10 industry portfolios formed from stocks traded on three major U.S. exchanges in the period between 1965 and 2002. The R^2s from the predictive linear regression models are in most cases between 15 and 20 percent.

Our empirical results suggest that this predictability is consistent with rational pricing. Although, in frictionless market we reject most of asset pricing models, which confirms the findings of Kirby (1998), this situation reverses as we incorporate market frictions. Given that the strategies, which exploit predictability, are usually rebalanced on the monthly basis, it is not surprising that monthly transaction costs of order less than 50 basis points reconcile the evidence of predictability in most of the cases. From all tested models only the CAPM in the unconditional version seems not to be consistent with rational pricing even after incorporating market frictions.

The evaluation of economic significance confirms the statistical tests. Hansen and Jagannathan distance measure decreases when we move from frictionless market to the market with frictions, which suggests that the incorporation of market frictions improve the performance of the models. In fact, even for the unconditional CAPM model, which was found inconsistent according to statistical tests, the distance decreases substantially when we incorporate 50 basis points transaction costs. Utility-based metric indicate similar patter. A mean-variance investor significantly overstates his utility gain (up to 6 percent per month) from return predictability that is not consistent with asset pricing models. When we incorporate market frictions these gains are substantially reduced. Additionally, we show that without economic evaluation, statistical tests may be inconclusive. We found that a mean-variance investor will significantly overestimate his utility gain from in-sample predictability even when it is consistent with the conditional CAPM.

4.A Deriving the restrictions with transaction costs

Below we derive the restrictions given in Section 4.3.2 that are imposed on the measures of predictability from a linear regression framework when transaction costs are present in the market. In such case the rational asset pricing models imply the following first-order conditions (see, for example, He and Modest (1995)):

$$\begin{aligned} \tau_A &\leq E_t\left[q_{t+1}r_{i,t+1}\right] \leq \tau_B, \\ \mu_z\tau_A &\leq E\left[q_{t+1}\left(\mathbf{z}_t r_{i,t+1}\right)\right] \leq \mu_z\tau_B. \end{aligned}$$

Define variables x_i such that $\tau_A \leq x_i \leq \tau_B$, $\forall i$. Without restricting x_i any further, we can write:

$$E\left[q_{t+1}r_{i,t+1}\right] = x_1 \tag{4.24a}$$

$$E\left[q_{t+1}\left(\mathbf{z}_t r_{i,t+1}\right)\right] = \mu_z x_2. \tag{4.24b}$$

From (4.24a) we get

$$\begin{aligned} x_1 &= E\left[q_{t+1}r_{i,t+1}\right] = Cov\left[q_{t+1}, r_{i,t+1}\right] + \mu_r \Leftrightarrow \\ x_1 - Cov\left[q_{t+1}, r_{i,t+1}\right] &= \mu_r. \end{aligned}$$

Similarly, from (4.24b) it follows that

$$\begin{aligned} \mu_z x_2 &= E\left[q_{t+1}\left(\mathbf{z}_t r_{i,t+1}\right)\right] = Cov\left[q_{t+1}, \mathbf{z}_t r_{i,t+1}\right] + E\left[\mathbf{z}_t r_{i,t+1}\right] \\ &= Cov\left[q_{t+1}, \mathbf{z}_t r_{i,t+1}\right] + Cov\left[\mathbf{z}_t, r_{i,t+1}\right] + \mu_z\mu_r. \end{aligned}$$

Substituting for μ_r gives

$$\begin{aligned} \mu_z x_2 &= Cov\left[q_{t+1}, \mathbf{z}_t r_{i,t+1}\right] + Cov\left[\mathbf{z}_t, r_{i,t+1}\right] - \mu_z Cov\left[q_{t+1}, r_{i,t+1}\right] + \mu_z x_1 \Leftrightarrow \\ \mu_z\left(x_2 - x_1\right) &= Cov\left[q_{t+1}, \left(\mathbf{z}_t - \mu_z\right) r_{i,t+1}\right] + Cov\left[\mathbf{z}_t, r_{i,t+1}\right]. \end{aligned}$$

Pre-multiplying both sides by Σ_{zz}^{-1} and noting that $\tau_A - \tau_B \leq (x_2 - x_1) \leq \tau_B - \tau_A$, or $-\Delta \leq (x_2 - x_1) \leq \Delta$, where Δ is the bid-ask spread, we obtain

$$-\Sigma_{zz}^{-1}\mu_z\Delta \leq \Sigma_{zz}^{-1}Cov\left[q_{t+1}, \left(\mathbf{z}_t - \mu_z\right) r_{i,t+1}\right] + \Sigma_{zz}^{-1}Cov\left[\mathbf{z}_t, r_{i,t+1}\right] \leq \Sigma_{zz}^{-1}\mu_z\Delta$$

which simplifies to

$$-\Sigma_{zz}^{-1}\mu_z\Delta \leq \beta_{i,uz} - \beta_{i,rz} \leq \Sigma_{zz}^{-1}\mu_z\Delta.$$

4.B Testing the restrictions with transaction costs

The Wald test statistic in the presence of transaction costs is defined as follows:

$$W_i = \min_{-\widehat{\Sigma}_{zz}^{-1}\widehat{\mu}_z\Delta \leq \lambda_{i,z} \leq \widehat{\Sigma}_{zz}^{-1}\widehat{\mu}_z\Delta} T\left(\lambda_{i,z} - \widehat{\lambda}_{i,z}\right)\left[\widehat{\Lambda}_{i,z}\right]^{-1}\left(\lambda_{i,z} - \widehat{\lambda}_{i,z}\right)'$$

The bounds of the constraints on parameter $\lambda_{i,z}$ contain two additional estimates: $\widehat{\Sigma}_{zz}$ and $\widehat{\mu}_z$ and we need to take into account their estimation error. We define new parameter $\widehat{\gamma}_i$:

$$\widehat{\gamma}_i = \begin{bmatrix} \widehat{\mu}_z \\ \widehat{\beta}_{i,uz} \\ \widehat{\beta}_{i,rz} \end{bmatrix},$$

and estimate the Wald test statistic in the following way:

$$W = \min_{h(\gamma_i)\leq 0} T\left(\gamma_i - \widehat{\gamma}_i\right)'\left[\widehat{\Gamma}_i\right]^{-1}\left(\gamma_i - \widehat{\gamma}_i\right),$$

where $\widehat{\Gamma}_i$ is the covariance matrix of $\widehat{\gamma}_i$, which can be calculated as the submatrix of the asymptotic variance-covariance matrix of the GMM estimator $\widehat{\theta}$ and restrictions are defined in such way that:

$$h\left(\widehat{\gamma}_i\right) = \begin{bmatrix} either \\ -\Sigma_{zz}^{-1}\widehat{\mu}_z\Delta + \widehat{\beta}_{i,uz} - \widehat{\beta}_{i,rz} \\ or \\ -\Sigma_{zz}^{-1}\widehat{\mu}_z\Delta - \widehat{\beta}_{i,uz} + \widehat{\beta}_{i,rz} \end{bmatrix},$$

depending on the relevant bound.

4.C The Hansen-Jagannathan distance measure

In Kirby (1998) the Hansen-Jagannathan distance is derived from a projection of a valid pricing kernel onto a space of all asset payoffs. Since in this study we are interested in the payoffs of the trading strategies that exploit predictability we derive this measure by projecting a valid pricing kernel on a subspace of asset payoffs, namely on payoffs attainable with that strategy. This projection takes the following form:

$$m^*_{t+1} = \phi^*_0 + \left(\mathbf{r}_{t+1} \otimes (\mathbf{z}_t - \mu_z)\right)' \phi^*_{rz}$$

where m^*_{t+1} is a valid pricing kernel, ϕ^*_0 is the intercept and ϕ^*_{rz} is the vector of slope coefficients. Substituting for $\phi^*_0 = 1 - \mu'_{rz}\phi^*_{rz}$ gives

$$\begin{aligned} m^*_{t+1} &= 1 + \left[\left(\mathbf{r}_{t+1} \otimes (\mathbf{z}_t - \mu_z)\right) - \mu_{rz}\right]' \phi^*_{rz}, \\ m^c_{t+1} &= 1 + \left[\left(\mathbf{r}_{t+1} \otimes (\mathbf{z}_t - \mu_z)\right) - \mu_{rz}\right]' \phi^c_{rz} \end{aligned}$$

where m^c_{t+1} is the candidate pricing kernel, $\mu_{rz} = E\left(\mathbf{r}_{t+1} \otimes (\mathbf{z}_t - \mu_z)\right),$ and the second relation follows by analogy. Finally, the distance can be calculated as

$$\begin{aligned} d^2 &= ||m^*_{t+1} - m^c_{t+1}|| = E\left[m^*_{t+1} - m^c_{t+1}\right]^2 \\ &= \left(\phi^*_{rz} - \phi^c_{rz}\right)' \Sigma_{rz} \left(\phi^*_{rz} - \phi^c_{rz}\right) \end{aligned}$$

where $\Sigma_{rz} = Var\left(\mathbf{r}_{t+1} \otimes (\mathbf{z}_t - \mu_z)\right).$

In order to express this distance with the measures of predictability note that:

$$\begin{aligned} \phi^c_{rz} &= \Sigma^{-1}_{rz} Cov\left(m^c_{t+1}, \mathbf{r}_{t+1} \otimes (\mathbf{z}_t - \mu_z)\right) \\ \phi^*_{rz} &= -\Sigma^{-1}_{rz}\mu_{rz} \end{aligned}$$

and by substituting above in the equation for the distance we get:

$$d = \left[\left(\mu_{rz} + Cov\left(m^c_{t+1}, \mathbf{r}_{t+1} \otimes (\mathbf{z}_t - \mu_z)\right)\right)' \Sigma^{-1}_{rz} \left(\mu_{rz} + Cov\left(m^c_{t+1}, \mathbf{r}_{t+1} \otimes (\mathbf{z}_t - \mu_z)\right)\right)\right]^{1/2}.$$

If we define $G = I_N \otimes \Sigma_{zz}$, and note that $\beta_u = G^{-1}\mu_{rz}$, and $\beta_r = -G^{-1}Cov\left(q_{t+1}, \mathbf{r}_{t+1} \otimes (\mathbf{z}_t - \mu_z)\right)$ we obtain the final representation of the distance measure:

$$d = \left[\left(\beta_{u,z} - \beta_{r,z}\right)' G \Sigma^{-1}_{rz} G \left(\beta_{u,z} - \beta_{r,z}\right)\right]^{1/2}.$$

4.D Figures and Tables

Table 4.1: **Definitions of industry portfolios**

Porftolio	**Four-digit SIC code**		**Portfolio Name**
	Panel A: 5 industry portfolios		
Manuf	2000-3999		Manufacturing
Utils	4900-4999		Utilities
Shops	5000-5999		Wholesale
	7000-7999		Retail
			and Some Services
Money	6000-6999		Finance
			Agric, Mines, Oil,
			Construction, Transport,
Other			Telecomunication,
			Health and Legal Services
	Panel B: 10 industry portfolios		
NoDur	0100-0999	2770-2799	Consumer
	2000-2399	3100-3199	NonDurables
	2700-2749	3940-3989	
Durbl	2400-2439	3714-3714	Consumer
	2500-2519	3716-3716	Durables
	2590-2599	3750-3751	
	3000-3099	3792-3792	
	3630-3659	3910-3939	
	3710-3711	3990-3999	
Oil	1200-1399		Oil, Gas, and Coal
	2900-2999		Extraction and Products
Chems	2800-2899		Chemicals and Allied Products
Manuf	2440-2499	3712-3713	Manufacturing
	2520-2589	3715-3715	
	2600-2699	3717-3749	
	2750-2769	3752-3791	
	3200-3629	3793-3909	
	3660-3709		
Telcm	4800-4899		Telephones and Television
Utils	4900-4949		Utilities
Shops	5000-5999		Wholesale, Retail,
	7000-7999		and Some Services
Money	6000-6999		Finance
Other			Everything Else

Table 4.2: **Descriptive statistics**

The table gives the descriptive statistics for industry portfolios and forecasting instruments. Panel A gives the information for the 5 portfolios. Panel B gives the same information for the 10 industry portfolios, and Panel C gives the information for instruments. First two columns give the average return (in %) and the standard deviation. The last 5 columns give the autocorrelation coefficients of order 1 month up to 12 months.

			Autocorrelations of order				
	Mean in %	**Std Dev**	**1**	**3**	**6**	**9**	**12**
			Panel A: 5 industry portfolios				
Manuf	1.27	6.53	0.21	-0.06	-0.03	-0.03	0.07
Utils	0.94	3.69	0.07	0.03	-0.01	-0.03	0.08
Shops	1.21	6.99	0.22	-0.04	-0.04	-0.02	0.07
Money	1.31	5.14	0.27	0.01	0.04	-0.01	0.14
Other	1.17	6.28	0.21	-0.04	0.00	-0.05	0.07
			Panel B: 10 industry portfolios				
NoDur	1.08	5.41	0.25	-0.03	-0.02	0.00	0.14
Durbl	1.17	6.51	0.23	-0.03	-0.02	-0.01	0.12
Oil	1.27	7.03	0.14	0.06	0.02	0.01	0.10
Chems	1.39	6.75	0.19	-0.07	-0.02	-0.03	0.03
Manuf	1.32	7.06	0.20	-0.05	-0.03	-0.03	0.07
Telcm	1.42	7.76	0.18	0.02	-0.02	-0.02	0.00
Utils	0.95	3.62	0.07	0.04	-0.01	-0.02	0.08
Shops	1.21	6.99	0.22	-0.04	-0.04	-0.02	0.07
Money	1.31	5.14	0.27	0.01	0.04	-0.01	0.14
Other	1.17	6.31	0.25	-0.06	0.00	-0.06	0.09
			Panel C: instruments				
Prem	1.04	0.44	0.97	0.89	0.80	0.72	0.63
Term	5.70	2.40	0.98	0.92	0.84	0.80	0.72
Div	3.39	1.23	0.99	0.97	0.94	0.91	0.87
Mkt	1.18	5.29	0.21	-0.04	-0.02	-0.03	0.09

Table 4.3: **Performance of industry returns**

The table gives the estimated Sharpe ratios (left block) for every industry (μ_r/σ_r) and the maximum Sharpe ratio that can be obtained by forming a portfolio consisting of the managed returns for every industry ($[\mu_{r\otimes z}\Sigma^{-1}_{r\otimes z}\mu_{r\otimes z}]^{1/2}$). In the middle block are reported the estimates of the α's from the regression of excess returns on factors ($r_{i,t+1} = \alpha_i + \beta_{i,f} f_{t+1} + \epsilon_{t+1}$). The content of the vector of factors f_{t+1} is dictated by the particular asset pricing model. For each industry return the test is based on a single regression of $r_{i,t+1}$, while for the managed returns, we test the joint significance of intercepts from (K) regressions of $r_{i,t+1} \otimes z_t$. Hence, for the joint tests and for the managed returns (left block) we only report the p-values from testing jointly the significance of α's. Panel A gives the results for the 5 industry portfolios and Panel B for the 10 industry portfolios. */** indicates significance level at 10/5 percent.

	Sharp Ratio			returns					managed returns			
	returns	managed		Unconditional		Conditional			Unconditional		Conditional	
		returns		CAPM	Factor	CAPM	Factor		CAPM	Factor	CAPM	Factor
				Panel A: 5 industry portfolios								
Manuf	0.12	0.34	α	0.31%**	0.26%**	0.25%*	0.06%	p	0.00	0.00	0.00	0.00
Utils	0.12	0.19	α	0.22%**	-0.02%	0.16%*	0.07%	p	0.06	0.09	0.07	0.12
Shops	0.10	0.36	α	0.24%	0.34%**	0.20%	0.01%	p	0.00	0.00	0.00	0.00
Money	0.15	0.35	α	0.47%**	0.12%	0.40%	0.02%	p	0.00	0.00	0.00	0.08
Other	0.10	0.36	α	0.23%*	0.12%	0.23%*	-0.03%	p	0.00	0.00	0.00	0.00
Jointly	0.17	0.56	p	0.03	0.08	0.13	0.89	p	0.00	0.00	0.00	0.00
				Panel A: 10 industry portfolios								
NoDur	0.11	0.38	α	0.22%*	0.00%	0.12%	-0.18%**	p	0.00	0.00	0.00	0.00
Durbl	0.10	0.37	α	0.22%	0.02%	0.12%	-0.19%**	p	0.00	0.00	0.00	0.00
Oil	0.11	0.26	α	0.38%*	0.00%	0.48%**	0.30%	p	0.00	0.03	0.02	0.47
Chems	0.13	0.30	α	0.43%**	0.44%**	0.41%**	0.31%**	p	0.00	0.00	0.00	0.10
Manuf	0.11	0.33	α	0.32%**	0.33%**	0.27%*	0.09%	p	0.00	0.00	0.00	0.00
Telcm	0.12	0.31	α	0.40%**	0.75%**	0.42%**	0.34%**	p	0.00	0.00	0.00	0.13
Utils	0.12	0.17	α	0.25%**	-0.02%	0.18%*	0.09%	p	0.23	0.21	0.38	0.24
Shops	0.10	0.36	α	0.24%	0.34%**	0.20%	0.01%	p	0.00	0.00	0.00	0.00
Money	0.15	0.35	α	0.47%**	0.12%	0.40%**	0.02%	p	0.00	0.00	0.00	0.08
Other	0.10	0.38	α	0.24%*	0.07%	0.19%	-0.15%*	p	0.00	0.00	0.00	0.00
Jointly	0.22	0.81	p	0.01	0.00	0.01	0.00	p	0.00	0.00	0.00	0.00

Table 4.4: **Predictability in industry returns**

The table presents the results of fitting a linear regression model in the following form:

$$r_{i,t+1} = \beta_{i0} + \beta_{i1} Jan_{t+1} + \beta_{i2} \Pr em_t + \beta_{i3} Term_t + \beta_{i4} Div_t + \beta_{i5} Mkt_t + \epsilon_{t+1}.$$

Panel A reports R^2s and estimated coefficients with p-values underneath, for the 5 industry portfolios. Panel B reports the same statistics for the 10 industry portfolios.

	Rsq	Intercept	Jan	Prem	Term	Div	Mkt	**Wald**	Wald
Panel A: 5 industry portfolios									
Manuf	16.18%	-0.06	0.07	1.48	-0.50	1.10	0.19	**80.23**	
(p)		0.01	0.00	0.01	0.00	0.01	0.00	**0.00**	
Utils	4.56%	0.00	0.02	1.20	-0.07	0.16	-0.02	**19.69**	
(p)		0.98	0.02	0.00	0.46	0.46	0.53	**0.00**	
Shops	16.99%	-0.08	0.07	1.99	-0.55	1.30	0.24	**89.34**	
(p)		0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	
Money	15.51%	-0.04	0.05	1.20	-0.46	0.86	0.16	**74.93**	
(p)		0.00	0.00	0.02	0.00	0.00	0.00	**0.00**	
Other	16.67%	-0.07	0.07	0.89	-0.46	1.29	0.20	**86.86**	198.11
(p)		0.00	0.00	0.14	0.00	0.00	0.00	**0.00**	0.00
Panel B: 10 industry portfolios									
NoDur	20.04%	-0.07	0.06	2.19	-0.47	0.99	0.20	**105.98**	
(p)		0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	
Durbl	19.26%	-0.07	0.07	1.96	-0.62	1.23	0.22	**90.00**	
(p)		0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	
Oil	5.39%	-0.02	0.04	-0.68	-0.32	1.03	0.08	**41.18**	
(p)		0.54	0.00	0.36	0.09	0.03	0.23	**0.00**	
Chems	10.16%	-0.05	0.06	1.32	-0.31	0.72	0.16	**58.28**	
(p)		0.02	0.00	0.03	0.03	0.14	0.01	**0.00**	
Manuf	15.66%	-0.06	0.08	1.28	-0.54	1.22	0.19	**75.79**	
(p)		0.01	0.00	0.05	0.00	0.01	0.00	**0.00**	
Telcm	9.92%	-0.05	0.06	1.58	-0.43	1.49	0.13	**56.83**	
(p)		0.05	0.00	0.02	0.02	0.01	0.08	**0.00**	
Utils	3.24%	0.01	0.01	1.05	-0.06	0.12	-0.04	**15.51**	
(p)		0.62	0.09	0.00	0.52	0.57	0.31	**0.02**	
Shops	16.99%	-0.08	0.07	1.99	-0.55	1.30	0.24	**89.34**	
(p)		0.00	0.00	0.00	0.00	0.00	0.00	**0.00**	
Money	15.51%	-0.04	0.05	1.20	-0.46	0.86	0.16	**74.93**	
(p)		0.00	0.00	0.02	0.00	0.00	0.00	**0.00**	
Other	20.14%	-0.08	0.07	1.56	-0.48	1.27	0.24	**102.30**	401.42
(p)		0.00	0.00	0.01	0.00	0.00	0.00	**0.00**	0.00

Table 4.5: **Tests of the restrictions in the frictionless market**

The table presents the estimates of the Wald statistics testing the null hypothesis that the differences between the unrestricted coefficients and the coefficients restricted by the PK are zero. The regression equation is:

$$r_{i,t+1} = \beta_{i0} + \beta_{i1}Jan_{t+1} + \beta_{i2}\Pr em_t + \beta_{i3}Term_t + \beta_{i4}Div_t + \beta_{i5}Mkt_t + \epsilon_{t+1}.$$

The results are based on the joint equality of all coefficients for each industry, and for the whole market. Panel A gives the information for the 5 industry portfolios, and Panel B gives the same information for the 10 industry portfolios.

	Frictionless market: Wald statistics				
	Mean-variance	Unconditional CAPM	Unconditional Factor	Conditional CAPM	Conditional Factor
	Panel A: 5 industry portfolios				
Manuf	59.32	68.94	41.83	34.97	4.75
(p)	0.00	0.00	0.00	0.00	0.58
Utils	13.71	14.85	13.28	6.22	3.89
(p)	0.03	0.02	0.04	0.40	0.69
Shops	63.36	76.10	45.36	36.92	3.83
(p)	0.00	0.00	0.00	0.00	0.70
Money	55.67	57.00	41.42	29.65	1.35
(p)	0.00	0.00	0.00	0.00	0.97
Other	57.23	71.05	42.04	39.33	5.40
(p)	0.00	0.00	0.00	0.00	0.49
Jointly	165.86	174.07	135.97	139.96	60.33
(p)	0.00	0.00	0.00	0.00	0.00
	Panel B: 10 industry portfolios				
NoDur	91.60	94.09	61.98	57.10	3.45
(p)	0.00	0.00	0.00	0.00	0.75
Durbl	81.34	84.15	51.54	49.12	3.46
(p)	0.00	0.00	0.00	0.00	0.75
Oil	25.10	25.44	14.15	13.75	3.23
(p)	0.00	0.00	0.03	0.03	0.78
Chems	45.88	42.82	30.47	20.57	5.20
(p)	0.00	0.00	0.00	0.00	0.52
Manuf	66.43	66.12	39.51	32.29	5.16
(p)	0.00	0.00	0.00	0.00	0.52
Telcm	36.17	39.15	27.75	14.30	1.82
(p)	0.00	0.00	0.00	0.03	0.94
Utils	10.49	9.48	9.53	3.82	3.67
(p)	0.11	0.15	0.15	0.70	0.72
Shops	72.35	76.10	45.36	36.92	3.83
(p)	0.00	0.00	0.00	0.00	0.70
Money	63.09	57.00	41.42	29.65	1.35
(p)	0.00	0.00	0.00	0.00	0.97
Other	82.62	88.07	54.90	51.61	7.02
(p)	0.00	0.00	0.00	0.00	0.32
Jointly	295.63	322.63	273.79	258.95	153.43
(p)	0.00	0.00	0.00	0.00	0.00

Table 4.6: **Tests of the restrictions with short sales constraints**

The table presents the estimates of the Wald statistics testing the null hypothesis that the differences between the unrestricted coefficients and the coefficients restricted by the PK are negative. The regression equation is:

$$r_{i,t+1} = \beta_{i0} + \beta_{i1} Jan_{t+1} + \beta_{i2} \Pr em_t + \beta_{i3} Term_t + \beta_{i4} Div_t + \beta_{i5} Mkt_t + \epsilon_{t+1}.$$

The results are based on the joint tests for all coefficients for each industry, and for the whole market. Panel A gives the information for the 5 industry portfolios, and Panel B gives the same information for the 10 industry portfolios.

Short sales constraints: Wald statistics

	Mean-variance	Unconditional CAPM	Unconditional Factor	Conditional CAPM	Conditional Factor
Panel A: 5 industry portfolios					
Manuf	47.45	59.33	31.31	33.27	3.72
(p)	0.00	0.00	0.00	0.00	0.24
Utils	13.18	14.73	12.86	5.08	3.39
(p)	0.00	0.00	0.00	0.14	0.27
Shops	48.41	63.56	33.01	33.63	3.46
(p)	0.00	0.00	0.00	0.00	0.26
Money	47.09	50.24	36.29	28.85	1.07
(p)	0.00	0.00	0.00	0.00	0.65
Other	47.60	62.72	31.87	37.43	4.48
(p)	0.00	0.00	0.00	0.00	0.18
Jointly	65.06	79.01	46.81	49.02	8.18
(p)	0.00	0.00	0.00	0.00	0.15
Panel B: 10 industry portfolios					
NoDur	80.68	86.09	55.54	55.49	3.45
(p)	0.00	0.00	0.00	0.00	0.26
Durbl	65.35	70.50	42.50	44.00	3.07
(p)	0.00	0.00	0.00	0.00	0.31
Oil	18.93	19.57	10.21	7.90	0.49
(p)	0.00	0.00	0.02	0.04	0.79
Chems	40.99	40.22	24.68	20.57	4.48
(p)	0.00	0.00	0.00	0.00	0.18
Manuf	51.92	55.28	27.57	30.27	3.64
(p)	0.00	0.00	0.00	0.00	0.25
Telcm	29.32	32.15	19.33	13.38	1.32
(p)	0.00	0.00	0.00	0.00	0.59
Utils	10.06	9.40	9.23	2.86	2.62
(p)	0.02	0.02	0.02	0.33	0.36
Shops	57.01	63.56	33.01	33.63	3.46
(p)	0.00	0.00	0.00	0.00	0.26
Money	52.48	50.24	36.29	28.85	1.07
(p)	0.00	0.00	0.00	0.00	0.65
Other	70.90	79.55	45.14	50.34	6.82
(p)	0.00	0.00	0.00	0.00	0.07
Jointly	94.73	100.86	61.23	66.83	10.15
(p)	0.00	0.00	0.00	0.00	0.17

Table 4.7: **Tests of the restrictions with transaction costs**

The table presents the estimates of the Wald statistics testing the null hypothesis that the differences between the unrestricted coefficients and the coefficients restricted by the PK fall within the bounds determined by transaction costs. The regression equation is:

$$r_{i,t+1} = \beta_{i0} + \beta_{i1} Jan_{t+1} + \beta_{i2} \Pr em_t + \beta_{i3} Term_t + \beta_{i4} Div_t + \beta_{i5} Mkt_t + \epsilon_{t+1}.$$

The results are based on the joint tests for all coefficients for each industry, and for the whole market. Panel A gives the information for the 5 industry portfolios, and Panel B gives the same information for the 10 industry portfolios. Left block of the table gives the results for transaction costs of order 12.5 basis points, and the right block for transaction costs of order 50 basis points.

	Transaction costs (12.5 bp): Wald statistics					Transaction costs (50 bp): Wald statistics				
	Mean-	Unconditional		Conditional		Mean-	Unconditional		Conditional	
	variance	CAPM	Factor	CAPM	Factor	variance	CAPM	Factor	CAPM	Factor
				Panel A: 5 industry portfolios						
Manuf	17.22	26.74	8.53	15.66	1.59	7.04	13.43	4.53	5.53	0.00
(p)	0.00	0.00	0.03	0.00	0.54	0.06	0.00	0.17	0.11	0.97
Utils	0.33	2.76	0.54	0.02	0.00	0.00	0.00	0.00	0.00	0.00
(p)	0.84	0.34	0.78	0.95	0.96	0.97	0.97	0.98	0.97	0.96
Shops	9.44	19.68	5.22	10.52	1.02	4.11	10.03	3.04	3.95	0.00
(p)	0.02	0.00	0.13	0.01	0.66	0.20	0.02	0.31	0.21	0.98
Money	13.94	15.84	9.20	8.30	0.01	1.87	5.18	2.66	0.95	0.00
(p)	0.00	0.00	0.02	0.04	0.96	0.48	0.13	0.36	0.67	0.97
Other	16.19	28.33	8.20	16.58	1.87	6.72	13.70	4.37	5.81	0.00
(p)	0.00	0.00	0.04	0.00	0.48	0.07	0.00	0.18	0.10	0.97
Jointly	18.00	28.49	9.78	16.75	1.87	7.06	13.92	4.53	5.85	0.00
	0.01	0.00	0.10	0.05	0.99	0.24	0.03	0.45	0.54	1.00
				Panel B: 10 industry portfolios						
NoDur	18.25	22.41	8.10	13.34	0.42	5.69	8.72	3.33	2.72	0.00
(p)	0.00	0.00	0.04	0.00	0.80	0.11	0.03	0.28	0.35	0.95
Durbl	21.07	24.16	8.78	14.41	0.59	9.13	11.98	4.32	4.46	0.00
(p)	0.00	0.00	0.03	0.00	0.75	0.03	0.01	0.19	0.18	0.95
Oil	7.84	10.62	4.99	4.19	0.03	1.36	2.65	0.35	0.14	0.00
(p)	0.04	0.01	0.14	0.20	0.93	0.58	0.36	0.83	0.89	0.97
Chems	18.47	20.87	10.06	11.87	2.50	7.22	9.58	4.95	3.55	0.12
(p)	0.00	0.00	0.02	0.01	0.38	0.06	0.02	0.14	0.25	0.90
Manuf	21.31	26.60	7.98	15.33	1.71	10.46	14.33	4.52	6.21	0.01
(p)	0.00	0.00	0.04	0.00	0.51	0.01	0.00	0.17	0.08	0.95
Telcm	5.20	8.39	2.80	3.19	0.09	1.93	3.66	1.65	0.83	0.00
(p)	0.13	0.03	0.34	0.29	0.91	0.47	0.24	0.53	0.71	0.97
Utils	0.00	0.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
(p)	0.97	0.70	0.98	0.97	0.97	0.97	0.97	0.98	0.97	0.97
Shops	13.42	19.68	5.22	10.52	1.02	6.16	10.03	3.04	3.95	0.00
(p)	0.00	0.00	0.13	0.01	0.65	0.09	0.02	0.31	0.21	0.95
Money	16.28	15.84	9.20	8.30	0.01	3.17	5.18	2.66	0.95	0.00
(p)	0.00	0.00	0.02	0.04	0.94	0.30	0.13	0.36	0.67	0.96
Other	27.28	34.72	11.20	22.03	2.86	13.03	17.88	6.27	8.74	0.09
(p)	0.00	0.00	0.01	0.00	0.33	0.00	0.00	0.08	0.03	0.90
Jointly	28.77	34.98	12.52	22.03	3.24	13.03	17.88	6.27	8.74	0.12
(p)	0.00	0.00	0.09	0.17	1.00	0.10	0.03	0.58	0.64	1.00

Table 4.8: **Threshold values of transaction costs**

The table gives the values of the transaction costs for which we cannot reject the null hypothesis that the difference between the unrestricted and restricted coefficients falls within a transaction costs bounds at the 10% significance level. The results are based on the joint tests for all coefficients for each industry, and for the whole market. Panel A gives the information for the 5 industry portfolios, and Panel B gives the same information for the 10 industry portfolios.

	Threshold values: basis points				
		Unconditional		Conditional	
	MV	CAPM	Factor	CAPM	Factor
Panel A: 5 industry portfolios					
Manuf	48	74	18	40	0
Utils	2	3	2	0	0
Shops	27	61	9	27	0
Money	27	40	18	14	0
Other	44	74	18	44	0
Jointly	31	57	9	13	1
Panel B: 10 industry portfolios					
NoDur	44	55	18	31	0
Durbl	57	70	22	35	0
Oil	14	22	4	0	0
Chems	48	57	27	31	0
Manuf	61	78	18	44	0
Telcm	9	18	6	2	0
Utilities	0	0	0	0	0
Shops	44	61	9	27	0
Money	33	40	18	14	0
Other	70	82	40	55	0
Jointly	44	57	9	7	1

Table 4.9: **Economic significance**

Panel A gives the Hansen-Jagannathan distance measures, which tests the mis-specification of the asset pricing models when market frictions are incorporated. Panels B and C give the differences in the certainty equivalent returns, which reflect a utility gain the investor cannot obtain from predictable returns, because the predictability is inconsistent with asset pricing models. Panel B is based on the in sample predictability, while Panel C is based on one period ahead predictability. The left block of the table gives the results for the 5 industry portfolios, and the right block for the 10 industry portfolios.

	Mean-variance	Unconditional CAPM	Unconditional Factor	Conditional CAPM	Conditional Factor	Mean-variance	Unconditional CAPM	Unconditional Factor	Conditional CAPM	Conditional Factor
	5 industry returns					10 industry returns				
Panel A: Hansen-Jagannathan distance measure										
Frictionless mkt	0.52	0.55	0.51	0.50	0.38	0.73	0.74	0.71	0.71	0.59
Short sales	0.34	0.36	0.34	0.28	0.14	0.40	0.39	0.37	0.30	0.16
Tr costs (12.5 bp)	0.14	0.17	0.18	0.12	0.04	0.16	0.18	0.19	0.13	0.06
Tr costs (50 bp)	0.09	0.12	0.13	0.08	0.00	0.11	0.13	0.14	0.09	0.01
Panel B: Differences in CER, in sample predictability										
Frictionless mkt	3.36%	4.13%	2.99%	3.69%	1.36%	6.19%	6.64%	5.61%	6.35%	3.31%
Short sales	0.71%	0.73%	0.60%	0.65%	0.24%	0.99%	1.16%	1.05%	1.06%	0.38%
Tr costs (12.5 bp)	3.66%	3.51%	2.98%	3.63%	1.26%	5.73%	5.79%	5.90%	6.60%	3.14%
Tr costs (50 bp)	3.21%	3.42%	2.78%	3.28%	1.30%	5.94%	5.79%	5.46%	6.52%	3.19%
Panel C: Differences in CER, out of sample predictability										
Frictionless mkt	0.04%	0.12%	0.04%	0.08%	0.08%	0.14%	0.29%	0.39%	0.30%	0.57%
Short sales	0.22%	0.38%	0.20%	0.16%	0.08%	0.21%	0.46%	0.28%	0.23%	0.22%
Tr costs (12.5 bp)	0.16%	0.14%	0.01%	0.15%	-0.01%	0.15%	0.40%	0.09%	0.29%	0.01%
Tr costs (50 bp)	0.09%	0.14%	0.02%	0.15%	-0.01%	0.04%	0.37%	0.10%	0.31%	0.06%

Figure 4.1: **Predictability (R^2) implied by the asset pricing models.**
This figure plots the unrestricted and the restricted by the PK R^2s from the following regression:

$$r_{i,t+1} = \beta_{i0} + \beta_{i1}Jan_{t+1} + \beta_{i2}\Pr em_t + \beta_{i3}Term_t + \beta_{i4}Div_t + \beta_{i5}Mkt_t + \epsilon_{t+1}$$

for all asset pricing models (z-axis) and for both the 5 and 10 industry portfolios (x-axis).

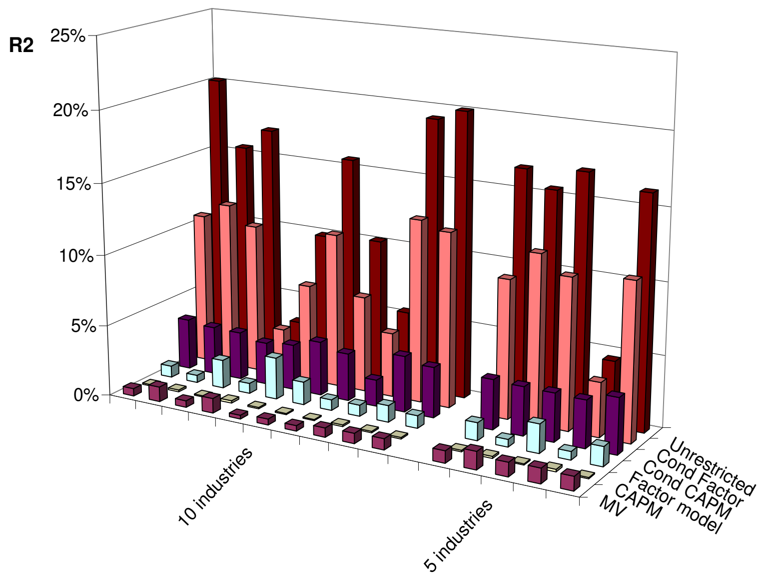
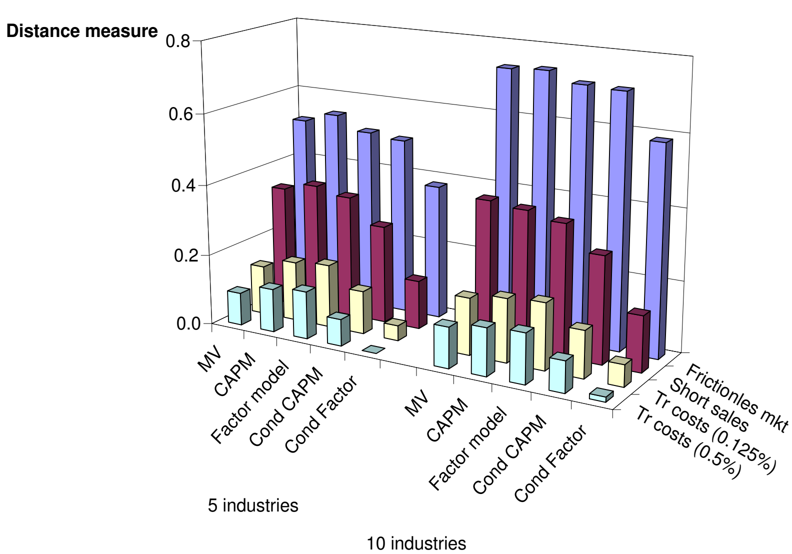


Figure 4.2: **Hansen-Jagannathan distance measure.**
This figure plots the estimated Hansen-Jagannathan distance measures for all asset pricing models and both the 5 and 10 industry portfolios (x-axis) and for all market specifications (z-axis): frictionless market, short sales constraints and transaction costs.



Chapter 5

Behavioral Factors in the Pricing of Financial Products

5.1 Introduction

There is ample attention in the financial literature for the question why market values of assets deviate from rational values. Cornell and Shapiro (1989) document episodes of significant overpricing in the Treasury bond market and potential arbitrage opportunities that cannot be attributed to changes in fundamentals. When clear rational explanations are absent, behavioral factors like framing and cognitive errors may play an important role. Rational financial decision-making should not be affected by the words that are chosen in finance proposals. However, recent studies confirm that the framing of the participation option in American 401(k) defined contribution pension plans as well as specific plan characteristics have important effects on the extent to which employees elect to join. Madrian and Shea (2001) find that participation increased sharply when a company introduced automatic enrollment, forcing employees to opt out if they did not want to participate. Similar results are reported by Mitchell and Utkus (2003). In the case of wrongly priced financial products it is generally very difficult to conclude whether the overpricing is caused by behavioral factors. The common approach is to investigate all possible rational factors and, if they do not explain the overpricing, to conclude that the deviation from the rational values is caused by behavioral factors. An important disadvantage of this approach is that it does not explicitly demonstrate the existence of behavioral factors. For this reason we take a different approach.

In this chapter we study the pricing of reverse convertible bonds. After establishing that these bonds are overpriced, we set up a financial experiment to study whether the overpricing may be explained by two behavioral factors: framing and cognitive errors.

A reverse convertible bond (RC) is a bond that can be exchanged into shares of common stock at the option of the issuer.[1] In fact, a reverse convertible bond is a bond in combination with a written put option. In order to compensate investors for the possible loss due to the written put option, the bonds carry very high coupon rates. These rates vary according to the conversion conditions and to the nature of the underlying shares; however, coupon rates as high as 20% have been observed in this market. Because of the high coupon interest, investing in plain vanilla reverse convertible bonds is somewhat less risky than investing in shares of common stock. At the same time the investment is much riskier than a bond investment, since at the maturity the issuer has the right to redeem either in cash or by delivering a fixed number of shares. This means that there is always a chance that the bond will not be redeemed at par. Some of the investors do not seem to realize the true riskiness of reverse convertibles. Ignoring the risk component has a significant impact on the perception of these products. Given that investors observe a high coupon rate, while they ignore the risk of a possible redemption of the bond below its par value, it becomes less surprising that reverse convertibles have gained a large popularity. The high yield that these financial instruments offer is especially attractive for investors in economies that offer low interest rates or in bullish markets where investors are more likely to underestimate the probability that the bond will be redeemed below its par value.

The popularity of RCs started in Europe, but has recently also spread to the United States. In August 2005, there were more than three thousand reverse convertible bonds publicly offered, traded and listed on the major European stock exchanges (Euronext,[2] Frankfurt, Zurich) and nearly 200 products were traded on the American Stock Exchange.[3] They are typically 2-3 year financial instruments that mostly have domestic shares as the underlying security. In some cases foreign shares, baskets of shares, or indexes form the underlying securities. Reverse convertible bonds are issued by large banks. These banks generally also act as market makers for their own products in a secondary market (Burth, Kraus, and Wohlwend (2001)). It is important to note that there are no arbitrage possibilities in this market, as investors are not able to short sell the reverse convertible bonds. Practical literature often suggest that these instruments

[1] In the past these bonds have also been issued under the name "Reverse Exchangeable Bonds". Recently the term "Reverse Exchangeable Securities" has become most popular (see also note 3). All these terms refer to what we define as reverse convertible bonds.

[2] Consolidation of the stock exchanges in Amsterdam, Brussels, Paris and Lisbon.

[3] In the U.S. the bonds are issued under different names: Reverse Exchangeable Securities issued by ABN AMRO, and Equity Linked Term Notes issued by City Group Global Markets Holdings.

are mainly bought by individual investors who are not aware of options, usually keep bonds in their portfolio and normally do not trade on the stock exchange. Another party that is present in this market are institutions that are legally restricted from investing in shares and options and use RCs to circumvent these regulations.

This chapter studies Dutch reverse convertibles issued from January 1, 1999 to December 31, 2002. We choose the Dutch market because in this market RCs and long-term options are popular with investors. This allows us to price the RCs as a combination of a bond and a put option. We find that, on average, the plain vanilla RCs are overpriced by approximately 6%, while the knock-in RCs seem to be priced fairly. The documented overpricing seems to be driven by the option component. It is confirmed in a model-free analysis and is persistent for approximately one fourth of the lifetime of the reverse convertibles. Moreover, the documented overpricing remains significant in each year within our sample period. Given that the number of issuances increased over the sample period, this shows considerable economic losses to the investors in this market.

As mentioned before, the purpose of this chapter is to study whether the overpricing can at least partly be explained from behavioral factors. This argument is grounded in the literature on behavioral finance, which shows that investors may not be "fully" rational in their decisions (see, e.g. Barber and Odean (2002, 2005)). They may rather be "under influence" and this bias may create market inefficiency in the shape of mispricing (Hirshleifer (2001); Barberis, Shleifer, and Vishny (1998)). Two behavioral factors that are mentioned in the literature are framing and probability judgement errors, hereafter to be referred to as cognitive errors. Framing occurs when a different representation of the same product yields a different price (Shefrin and Statman (1993)). Cognitive errors occur when investors underestimate the probability that the bonds will be converted into equity, because they mistakenly believe that an increasing historical stock price pattern will continue into the future.

In order to test whether these behavioral factors play a role, we design a financial experiment. In this experiment participants receive information for pricing a simple financial product with similar characteristics as a reverse convertible bond. However, we present the information differently for four groups. First, the framing effect is tested. This is done by providing half of the participants with a positive framework in which it is stated what happens if the price of the underlying shares goes up. The other half of the participants is provided with a negative framework for the stock price. Similarly we test for the existence of cognitive errors by providing half of the participants with an increasing historical stock price pattern. The other half is presented with a decreasing historical stock price pattern. Our results suggest that framing and cognitive errors, play an important role in the pricing of the simple financial product. Although the simple financial product is not exactly similar to a reverse convertible, our results shed some light on the ability of framing the redemption and the past stock price behavior to affect the pricing of the reverse convertible bonds.

The remainder of this chapter is organized as follows. Section 5.2 contains the data and the methodology. In the following Section 5.3 we present the results and in Section 5.4 we discuss possible explanations. In the latter section we also present the financial experiment and the results of this experiment. Finally, we conclude in Section 5.5.

5.2 Data and Method

5.2.1 Previous empirical research

Despite the large extent of the market for hybrid products, there has been very little empirical research on this topic until now. Wilkens, Erner, and Röder (2003) study discount certificates and reverse convertibles in Germany. Discount certificates very much resemble reverse convertibles. With the purchase of a discount certificate the holder acquires a bundle of shares at a "discount" compared to the current market price. At the maturity date these shares are delivered to the holder if the total value of the shares does not exceed a pre-specified maximum repayment amount. Otherwise, the certificate pays this pre-specified amount in cash. Wilkens, Erner, and Röder (2003) study daily quotes of reverse convertibles and discount certificates in November 2001. They find an average overpricing of 3.04% of reverse convertibles and 4.20% for discount certificates over replication strategies that use options. Burth, Kraus, and Wohlwend (2001) study the same financial instruments for Switzerland. They compare issuance prices, derived from the issuers' published term sheets, with replication strategies that use options. They find an average overpricing for reverse convertibles of 3.22% and for discount certificates of 1.40%. Finally, Stoimenov and Wilkens (2005) study the pricing of a large number of different equity-linked products in the German market. They find that these products are, on average, priced above their theoretical values. The average overpricing for the different products varies between 1.45% and 5.17%.

This study differs from other research on the pricing of reverse convertible bonds and other structured products in two important ways. The first difference is based on the fact that in the Netherlands long-term call options are traded on the options exchange. In the U.S. the market for long-term call options is not very liquid, which causes a puzzle about the levels of implied volatilities of listed options (see e.g. Bollen and Whaley (2004)). However, this is not the case for the Netherlands, where there is a very active market in long-term call options.[4] In some cases this allows us to conduct a model-free analysis by directly comparing reverse convertibles to combinations of put options traded on the options exchange, and bonds. The second difference is that we explicitly study whether the overpricing can be explained by behavioral factors using a financial experiment.

5.2.2 Method

Reverse convertible bonds (RCs) are bonds that can be exchanged into shares of common stock at the option of the issuer. Therefore, they are in fact a combination of a bond and a written put option. The model price of a reverse convertible has two components. The first component is an otherwise identical bond issued by the same issuer, without the option for the issuer to pay back the bond by delivering shares. The second component is the value of the embedded put options. The premium induced by these written put options is reflected in the price of the reverse convertibles by reducing the value of the bond with the put value in the following way:

$$Price(reverse\ convertible\ bond) = Price(coupon\ bond) - Price(put\ options).$$

The number of put options is specific for each reverse convertible and is defined by the conversion rate.

In order to examine whether reverse convertibles are overpriced, we follow two approaches. In the first approach we calculate the value of the put option using an option pricing model. Next to this model-based approach we also use a model-independent approach. We estimate the value of the put option, which is included in the RC, as the value of an options-exchange traded put option with a similar exercise price and maturity as the implicit put. This approach can only be used for a relatively small number of cases, since we cannot match all reverse convertibles with options data. Hence, we also use the put-call parity to infer the value of the put premium directly from the observed call prices. For both approaches we need to calculate a price of the bond involved in the reverse convertible.

We define overpricing as the difference between the full market price and the model

[4] See note 11.

price relative to the model price:

$$Overvaluation = \frac{Full\ market\ price - Model\ price}{Model\ price} 100\%.$$

The full market price consists of the price that is quoted at a certain date plus the accrued coupon payments. The model price is derived from the price of a bond and a written put option, instruments that are embedded in reverse convertibles. When the result is negative we conclude that there is an underpricing.

Bond part

We need to calculate a model price of the bond part of reverse convertibles, because non-convertible bonds with coupon payments as high as the ones observed for the reverse convertibles are not traded in the market. We use a standard discounted cash flow approach, in which the price of a coupon-paying bond can be expressed in the following way:

$$P = \sum_{t=1}^{m} \frac{I}{(1+k)^t} + \frac{F}{(1+k)^m}, \tag{5.1}$$

where t is the time when the coupon is paid, m is the maturity time, F is the Face Value of the bond, I is the amount of coupon paid, and k is the bond specific effective yield.

Option part

In order to derive a premium for writing put options we use the prices of the options that are traded in the market and have the same characteristics as the reverse convertibles.

In cases where we are not able to find such options traded, we calculate the model price of the options. We use the Constant Elasticity of Variance (CEV) model of Cox and Ross (1976) with the following diffusion process:

$$dS/S = \mu dt + \sigma S^{(\beta-2)/2} dW, \tag{5.2}$$

where S is the price of the underlying stock, μ is the expected rate of return on the stock, W is the Brownian Motion, $(\beta - 2)$ is the elasticity of variance with respect to the price, σ is the volatility of the stock price returns given by the following equation: $\sigma(S, t) = \sigma S^{(\beta-2)/2}$.

This class of models constitutes a relevant framework for our research because it allows for testing several specifications of the relation between the dynamics of option volatility and stock price dynamics. We use two special cases of CEV models, i.e. when

$\beta = 2$ the Black and Scholes (1973) model, where the volatility of the underlying asset is assumed to be constant during the life-time of the option; and when $\beta = 1$ the Square Root model (Cox and Ross (1976)), where the volatility and the price of the underlying asset are inversely related. The latter is supported by several theoretical papers, see e.g. Boyle and Emanuel (1980) and Schroder (1989).[5] Both models are corrected for continuous dividend payments (Merton (1973)). Some of the RCs in our sample include knock-in options. These can be valued using a variant of the Black-Scholes model that is derived for such barrier options.[6]

5.2.3 Data Description

We analyze a sample of reverse convertibles that were issued from January 1, 1999 to December 31, 2002, that are listed on Euronext Amsterdam (the Amsterdam Stock Exchange), and for which long-term call options are outstanding. The reverse convertibles were identified from the financial newspaper *De Officiële Prijscourant van de Effectenbeurs* (the official newspaper of the stock exchange).

The sample consists of plain vanilla reverse convertibles (RCs) and several variations, such as knock-in RCs, and knock-out RCs. A "knock-in" RC initially starts as a "normal" bond and when the price of the underlying hits a pre-specified barrier it becomes a reverse convertible. A "knock-out" RC works in the opposite direction. It starts as a plain vanilla reverse convertible but it turns into a "normal" bond after the pre-specified barrier has been reached. The risk of a payoff in shares only arises if the price crosses ("knock-in") or does not cross ("knock-out") the barrier. Consequently, this risk is lower compared to a plain vanilla RCs. The idea of pricing "knock-in" and "knock-out" RCs is equivalent to the plain vanilla RCs, but instead of simple put options we need to use barrier options.

The sample consists of 108 reverse convertibles with a maturity of two years. The sample can be sub-divided into three groups: plain vanilla RCs, "knock-in" RCs and "knock-out" RCs. More details on the descriptive statistics of the sample are given in Panel A of Table 5.1.

[5] Boyle and Emanuel (1980) mentions two arguments for the use of a model in which the volatility is inversely related to the stock value, i.e. operating and financial leverage. The former is based on the fact that an increase in the stock price may reduce the variance of the stock's returns through the reduction of the debt to equity ratio even when a firm has almost no debt. The latter argument stems from the fact that since every firm faces fixed costs a decrease in income will decrease the value of the firm and increase its riskiness.

[6] See Hull (2003, page 439-441) for a description of this variant.

There are four banks issuing the reverse convertibles in our sample. These are ABN AMRO, Fortis Bank, ING Bank, and Rabo Securities. There are 47 plain vanilla RCs, the majority of which are issued by either ABN AMRO (21) or ING Bank (16). Rabo Securities has issued 29 knock-in RCs and Fortis Bank has issued 14 out of the 54 knock-in RCs. Apparently, the issuers in our sample are specializing either in the plain vanilla RCs or in the knock-in RCs.

Most of the characteristics of reverse convertibles are derived from the prospectuses. Market prices, trading volume and interest rates are retrieved from Datastream. In cases when we have information on options but prices and trading volumes of reverse convertibles are missing in Datastream we gather this information from De Officiële Prijscourant van de Effectenbeurs.

For several reasons we do not treat the issue price given in the prospectuses as the market value of reverse convertibles. First, not all prospectuses mention such a price. Second, in case it is mentioned, the issuers do not consider it to be binding. Finally, some of the RCs are not actively traded directly after the issuance. Therefore, we take the first trading price at which Datastream reports a positive volume as an issue price. Moreover, we take a window of five days at which Datastream reports a positive trading volume in order to avoid the possibility that the results will be driven by nonsynchronous trade of reverse convertibles, stocks or options.

5.2.4 Estimation Procedure

Pricing bond component

In order to price the bond part of the RCs we use the following variables: (1) the amount of the coupon paid (I), (2) the dates when the coupon is paid (t), (3) face value of the bond (F), (4) time to maturity (m), and (5) the bond specific effective yield (k).

The first four variables are derived from the respective issuance prospectuses of the RCs. A fact that complicates the pricing of bonds is the impossibility of observing the effective yield in the market directly. A reverse convertible bond is usually issued by a bank. This implies that a premium needs to be incorporated in order to reflect the credit risk. Such a premium is specific for each institution and each financial instrument. This rate is proxied for each issuer by calculating at each point in time the average credit spread (r_c) induced by a cross section of non-convertible bonds with the same maturity as RCs but different coupon payments (including zero coupon bonds). The spread for each bond is calculated as the difference between the yield on the bond and the appropriate risk-free rate proxied by the yield on government zero-coupon bonds. The horizon of the bond and the risk-free rate is matched on a monthly basis.[7] Finally, the bond specific yield (k) is the sum of the risk-free rate (r_f) and the average credit spread (r_c):

$$k = r_f + r_c. \tag{5.3}$$

Pricing option component

To price the option part of the RCs we use the following variables: (1) price of the underlying stock (S), (2) strike price (K), (3) time to maturity (m), (4) dividend yield (q), (5) the risk-free interest rate (r_f), and (6) the volatility of the returns on the underlying stocks (σ).

The first four variables are retrieved from Datastream. The fifth variable, the risk-free rate, is approximated as the average yield on government bonds with a maturity of 2 years.[8] The final variable, the volatility, needs to be estimated. A large body of literature has shown that the implied volatility[9] is superior to the historical, data-based forecasts.[10] For this reason we use the implied volatility.

To price the put option embedded in the reverse convertibles we need the volatility implied by long-term options. For this purpose either long-term call or put options can be used. There are two disadvantages of using long-term put options: (1) long-term put options traded in Amsterdam are of the American type, but the put options that we need to value are of the European type; (2) long-term put options can be very illiquid, implying that the implied volatility is unreliable. We use long-term call options as they suffer less from these drawbacks, i.e. early exercise is less likely and they are often more liquid.[11]

The information on the long-term call options is retrieved from Datastream. Since,

[7] For example, if the bond matures in January 2002 the spread in January 2000 is calculated as the difference between the yield on this bond and the 2-year risk-free rate. In February 2000 the 1 year and 11 months risk-free rate is used and so on.

[8] See e.g. Hull (2003, page 247).

[9] Implied volatility is often referred to as "market's volatility forecast".

[10] See e.g. Schwert (1990), and Amin and Ng (1997).

[11] For the underlying stocks in our sample, on average, the trading volume of long-term call options was higher then that of long-term put options. In the U.S. the market for long-term call options is not very liquid, which causes a puzzle about the levels of implied volatilities of listed options (see e.g. Bollen and Whaley (2004)). However, this is not the case for the Netherlands, where there is a very active market in long-term call options. For example, we calculate the average daily trading volume for options on Fortis and we find that they are equally liquid as short-term options. The average daily trading volume is 128.14 contracts per day (of each 100 options) for short-term options, and it is 119.74 contracts per day for long-term options.

the maturity and the strike price of the reverse convertibles do not match exactly with those of the options,[12] we use a weighted average of implied volatilities with respect to time to maturity and strike price (see, e.g., Ter Horst and Veld (2006)). We use two different estimates for the implied volatility. The first is based on the Black-Scholes model, while the second is based on the Square Root version of CEV model. Finally, the information on the prices of the RCs is derived from Datastream. In case the information on the RCs is not available in Datastream, the data-set is completed with quotes published in the official newspaper of the stock exchange.

5.2.5 Summary of the sample

Our original sample of 108 reverse convertibles that were issued from January 1, 1999 to December 31, 2002, that are listed on Euronext Amsterdam, and for which long-term call options are outstanding, is reduced for several reasons (Panel B of Table 5.1). First, 18 reverse convertibles are excluded because it is not possible to find information on prices and trading volume for RCs and the underlying options. Second, 15 observations are excluded because we cannot identify 5 days at which a price for the RC with a positive trading volume was quoted. In total we are able to price 75 reverse convertibles (70% of the original sample) where 32 were plain vanilla RCs (68%) and 43 are knock-in RCs (80%). There are no knock-out RCs left in our sample, since they all do not fit the selection criterion that there needed to be at least five trading days with a positive trading volume. The summary statistics for the final sample are presented in Table 5.2.

The sample consists of two groups of reverse convertibles: plain vanilla RCs and knock-in RCs. The average price for the plain vanilla RCs is 103% while for the knock-in RCs it is 98%. Both groups of contracts are actively traded; the average daily trading volume for plain vanilla reverse convertibles is approximately 190 million and for the knock-in reverse convertibles it is approximately 230 million. The average conversion ratio is 85 and 81 shares per contract for plain vanilla RCs and knock-in RCs respectively, which means that on average a plain vanilla can deliver more shares. The average barrier level for knock-in reverse convertibles is 78% of the conversion price. This means that on average when the price of the underlying stock drops by 22% a normal bond is converted into a reverse convertible bond.

[12] This can lead to a "volatility smile" (implied volatility as a function of its strike price) and "volatility term structure" (implied volatility as a function of its time to maturity), see e.g. Hull (2003, page 334-336).

5.3 Results

Recall that in order to examine whether reverse convertibles are fairly priced we compare the model price with the observed market price. The full market price consists of the price that is quoted at a certain date plus the accrued coupon payments. The model price is derived from the value of a bond and a written put option. In order to determine this model price, we follow two different approaches as discussed in the previous section. We first discuss the results for the model-based value of the put option. In this approach the option premiums are based on estimated option values based on the option pricing model of Black and Scholes (1973) and on the Square Root model of Cox and Ross (1976). In the second approach the market value of the put option is based on observed prices of long-term options.

5.3.1 Model-based value of the put premium

In order to calculate the value of the overpricing we need to use option-pricing models. We calculate the overpricing for all reverse convertibles in our sample using the Black-Scholes model. The results are given in Panel A of Table 5.3.

From this panel it appears that on average reverse convertibles are overpriced by 2.21% with a median of 1.55% and this overpricing is significant at the 1%-level. The average overpricing for the plain vanilla RCs is 5.92% with a median of 5.63% (significant at the 1%-level), while knock-in RCs are not overpriced, i.e. on average they are underpriced by -0.62%, but this value is not statistically different from zero.

At first, the fact that the plain vanilla RCs are more overpriced than knock-in RCs may appear to be surprising as more complex products (e.g. knock-in) could be expected to trade above the fair values. However, this result is consistent with previous findings in Stoimenov and Wilkens (2005), who find complex products to be both significantly more and significantly less overpriced than the simple equity linked products in the German market. Also, consistent with this finding is the earlier reported larger trading volume for knock-in RCs. This result is likely to stem from the differences in the option embedded in reverse convertibles. It seems that the option component constitutes a larger portion of the value for the plain vanilla RCs than for the knock-in RCs. First, for the knock-in RCs the option part becomes active only after the barrier level is reached, which in our sample will only occur when the stock price of the underlying drops by 22% on average. Furthermore, the difference between the market price of the reverse convertible bond and the theoretical price of an otherwise identical non-convertible bond (i.e. when the option value is assumed to be zero) is more negative for the plain vanilla (-9.3%) than for the knock-in RCs (-7.8%). This suggests that the overpricing seems to be entirely driven by the option component and that the value of the option for the plain vanilla must be larger than for the knock-in RCs.

In order to check the robustness of our results we additionally use the Square Root version of the CEV model, which captures the empirically observed inverse relation between volatility and stock price and thus fits the market data better than the Black-Scholes model. Empirical research by Lauterbach and Schultz (1990), and Hauser and Lauterbach (1997) finds that this is the most suitable model for the pricing of warrants.[13] Due to the fact that there is no closed form solution for the price of the barrier options using the Square Root version of the CEV model we can only compare the results for plain vanilla reverse convertibles. These results are shown in panel B of Table 5.3. As can be read from this panel the differences between the overpricing estimated with both models is negligible. The overpricing of the plain vanilla RCs is 5.87% with the Square Root model, while it is 5.92% for the Black-Scholes model, both significant at the 1%-level.

5.3.2 Model-independent value of the put premium

The market value of the put premium can also be determined on the basis of long-term options with a strike price and a maturity identical to those of the reverse convertibles. Since long-term barrier options are not traded on the options exchange of Euronext in Amsterdam, we are only able to calculate the market value of the put options for plain vanilla RCs.

We are not able to match exactly the maturity of the options with the maturity of RCs. Instead, we use options with a shorter maturity than reverse convertibles. Note that these options will have a lower price than the options embedded in RCs. By choosing such options we increase the model price of RCs and hence decrease the possible overpricing.

Among the options that have a shorter maturity than the RCs we were able to find 8 options, which had exactly the same strike as the RCs (exactly matched strike), and 10 options with a strike price that was very close but not identical to the strike of the RCs (closely matched strike). Panel A in Table 5.4 presents the results.

It appears that on average plain vanilla RCs are overpriced by 5.11% with a median of around 5.05% and this overpricing is significant at the 1%-level. This result is

[13]Warrants are relevant for us, because they are long-term options, just like the ones that we consider.

very close to the model-based results obtained for the plain vanilla RCs as reported in Table 5.3. However, in contrast to these model-based results we do observe two plain vanilla contracts to be underpriced. The difference in the overpricing between the options, which were exactly matched with the strike of the reverse convertibles and those that were less precisely matched is not statistically significant.

Additionally, instead of calculating the implied volatility based on long-term call options and then pricing the put option, we can use the put-call parity to calculate the put prices directly from the observed call prices. The put-call parity holds under the assumption of no-arbitrage possibilities, hence we do not assume any option pricing model here. In this sense this method can give us an indication of the robustness of our results. Because of the fact that the long-term barrier call options are not traded in Amsterdam, we can again only compare the results for plain vanilla reverse convertibles. These results are included in Panel B of Table 5.4. From this panel it can be seen that the difference between the option prices calculated using option pricing models and option prices derived from call options is again small. The average overpricing is 7.25% according to this approach and it is significant at the 1%-level, but it is less than 2 standard errors from the value of 5.92% for the model-based approach.

The results presented so far do not depend on any option pricing model, however they still depend on the estimate of the discount rate used in the valuation of the bond part. Table 5.5 presents the results of the average threshold value of the discount rate that is needed to equate the market prices with the theoretical prices of reverse convertibles (i.e. for which the overpricing is zero). It appears that a discount rate between 2% and 2.5% is required to equate the market prices with their theoretical counterparts. For comparison reasons, we present in Panel C the average values of the discount rate used in our sample (4.71%) and the average value of a risk-free rate (4.39%). This shows that the estimation error present in the discount rate is unlikely to generate the documented overpricing. Moreover, for 6 reverse convertibles we still find significant overpricing even when we use a highly unrealistic discount rate of 10 basis points.

5.3.3 Persistence of the overpricing

The results presented until now are based on the prices observed directly after the issue of reverse convertibles. In order to see whether the overpricing is a short-lived phenomenon we calculate the overpricing during the whole maturity of RCs. Since knock-in RCs are not overpriced we proceed with analyzing the plain vanilla reverse convertibles.

Figure 5.1 shows the relation between the average overpricing of plain vanilla reverse convertibles and their remaining time to maturity. It indicates that the reported overpricing is persistent for almost half a year after the issuance of the reverse convertibles. It is important to notice the difference between the initial overpricing of the reverse convertibles and the excess returns investors make on average when investing in Initial Public Offerings (IPOs) of common stocks. Given that common stock IPOs are on average underpriced (Ritter (2003)), investors generally have an opportunity to invest prior to the IPOs at a significantly lower price. Therefore, they stand to gain considerable profits. This is not the case for the reverse convertible bonds, as they are issued by trade, i.e. no reverse convertibles are sold before the first trading date and hence there is no investor that can benefit from the initial overpricing. Also contrary to IPOs we see that the overpricing persists for almost half a year after the issuance. After that the overpricing gradually starts to disappear. For at least two reasons, this is in line with our expectations. The first reason is that the life span of a reverse convertible is limited. At the end of its maturity, the value of the reverse convertible is by definition equal to either the nominal value of the bond, or the value of the common stock equivalent, whichever is lower. This means that the overpricing by definition should disappear. The second reason is that in the beginning of the bond's maturity, the banks will act as sellers. During that period the bonds are overpriced. At the end of the maturity, banks are more likely to be buyers, since they promise to maintain a market in these instruments. Given their expertise, they are not likely to overpay.

To analyze the overpricing during the sample period Table 5.6 gives the results per calendar year. This table shows that the overpricing per year varies between 0.89% and 5.05%. Although the magnitude of the overpricing has decreased over the sample period (though not monotonically), it still remains significant at the 10%-level at the end of the sample period. The second column presents the number of issues in each year. This column shows that there are more issues in 2002 than in 1999 that were significantly overpriced. This is contrary to the market-wide learning hypothesis, in which case we would expect a decrease in popularity of reverse convertible bonds.

5.4 Discussion and Financial Experiment

5.4.1 Rational explanations

In this chapter we document a significant overpricing of the plain vanilla reverse convertible bonds, of on average 5.92%. Even though the purpose of this study is to study whether at least part of the overpricing can be explained from behavioral factors, we should mention that it is possible that part of the overpricing can be explained from rational factors.

An obvious potential rational explanation that has to be studied are taxes. However, it is very unlikely that taxes play a role because reverse convertible bonds were taxed very unfriendly in the tax system, which prevailed until 2001. In that tax system, the whole coupon payment on the bond was taken into account as interest. This interest was taxed at the same progressive tax rate as, for example, income from employment.[14] This was criticized by the issuing banks, which argued that potential capital losses, because of redemption in stocks, were not tax deductible.[15] From 2001 the taxation of interest and dividend income was replaced in the Netherlands by a wealth tax. This also solved the problem of the unfriendly taxation of reverse convertible bonds.[16] In any case this shows that taxation is not an explanation for the overpricing of reverse convertibles.

The second rational factor that can be mentioned is the fact that we derive implied standard deviations from American options that are used to price European options. For this reason it is likely that the option premiums are biased upwards. This in turn leads to an underestimation of the model price of the RC and therefore to an overestimation of the overpricing. To minimize this bias, we use long-term call options, as they are less likely to be early exercised.

Another explanation can stem from the absence of arbitrage possibilities, as investors are not able to short sell reverse convertible bonds. Thus, investors are not able to exploit the observed overpricing. However, this does not explain the existence of overpricing. The fact that perfect arbitrage is not possible should not stop other market forces from correcting the prices, for instance supply-demand force should drive prices around their fundamental levels.

Finally, transaction costs may play a role since we compare a strategy that buys one instrument (reverse convertible) to the strategy that involves two instruments (bond and option). In principal, the transaction costs associated with the second strategy will be higher, and hence we may observe the overpricing if we ignore these costs.

Given the difficulty in enumerating and quantifying all rational explanations we suggest an alternative approach. We test explicitly whether behavioral factors may play

[14] There was a tax exemption for interest income of 1,000 guilders per person (approximately 455 euro).

[15] See Bierlaagh (1999) for a detailed discussion of the taxation of reverse convertible bonds in the Netherlands before January 1, 2001.

[16] See Meussen (2000) for a detailed description of the income tax system that prevails in the Netherlands from January 1, 2001.

a significant role in explaining the documented overpricing. If we can demonstrate that behavioral factors are important, then this also leads to the conclusion that rational factors alone are not sufficient to explain the overpricing.

5.4.2 Behavioral explanations

The behavioral finance literature may supply possible reasons for the documented overpricing. There exists a large body of literature within this field that looks at the effects of frames on choices.[17] Framing is a part of a decision process undertaken by a prospect theory investor (Kahneman and Tversky (1979)). In this theory, a decision is described as the evaluation of the potential gains and losses relative to some reference point. Authors distinguish between two sequential operations that lead to such a decision: an editing stage and an evaluation stage. The former phase consists of preliminary analysis and simplification of the choice problem. This can lead to Thaler's mental accounts (Thaler (1985)), where gains and losses are kept in separate mental accounts. Creation of such accounts can be influenced by the way the choice problem is presented, for instance, different reference points for comparing the outcomes, different definition of the choice problem that are associated with different emotions. Tversky and Kahneman (1986)) and many others,[17] show that the presentation of logically identical decision problems had large framing effect on choices. The latter stage of decision problem involves the application of decision rules to the framed accounts. The choices are evaluated and the one of highest value is selected. Shefrin and Statman (1993) show that the framing effect, among other behavioral finance reasons, has led to the success of covered calls.

We believe that this framing effect is also present in RCs. The strategy of buying a bond and writing a put option is now presented as a strategy of buying a high-yield bond. The Dutch financial newspaper *Het Financieele Dagblad* of February 1, 2003 gives the following quote from a press release of the ING bank of a reverse convertible bond on Ahold: *"A two-year bond with a coupon interest of no less than 15% per year with the additional prospect of receiving a solid package with shares of Ahold"*. Investors often do not see that a RC is a combination of a bond with a written put option. In an article in the same financial newspaper of August 1, 2000 it is argued by a derivatives specialist: *"A lot of investors actually do not see that a reverse convertible consists of two products. They often think that it is a bond with a high coupon interest and that they can decide themselves what will happen at the end of the maturity"*. In a newspaper

[17]See, for instance, Kahneman and Tversky (1979), Shefrin and Statman (1993), Madrian and Shea (2001), Mitchell and Utkus (2003), and Weber, Keppe, and Meyer-Delius (2000).

article of February 12, 1999 the same specialist also argues: *"Options only deter (..). However, if you combine it with a stock or a bond, or if you give it a beautiful name, people are often willing to buy it"*. This strengthens the idea that framing matters. In the last mentioned article the specialist also argues that RCs are mainly bought by investors who are not aware of options. Another derivatives specialist mentions that RCs are mostly bought by "bond investors" who normally do not trade on the stock exchange.[18] Kim and Zumbansen (2002) describe a court case in Germany where a plaintiff claimed compensation from a bank for the losses incurred in buying reverse convertibles. The plaintiff argued that he was not properly informed about the nature and risk of the transaction.

A second behavioral element in the design of financial products is the existence of cognitive errors (Kahneman and Tversky (1982); Shefrin and Statman (1994)). In this context Shefrin and Statman (1993) refer to the market of LYONs that existed in the United States in the beginning of the 1980s. LYONs are zero-coupon, convertible, callable and puttable bonds. These bonds were very popular in times of high interest rates. However, when interest rates started to fall, the issuers started to use the call features of the bonds. This led to a quick disappearance of the market for LYONs. According to Shefrin and Statman (1993) some of the investors who bought LYONs overestimated the probability that they would not be called, perhaps because they were not called in the recent past. The authors refer to this as cognitive errors. Another example of cognitive errors is presented by Clarke and Statman (1998), who find that writers of investment newsletters become optimistic after increases in stock prices and pessimistic after decreases. Like the previous example, this is based on the tendency to extrapolate recent stock movements, which is an example of representativeness heuristic. We expect that cognitive errors also play an important role in the overpricing of reverse convertibles since according to the earlier quoted derivatives specialist the market for RCs experienced a temporary decrease in demand from investors after the first RCs were redeemed in shares rather than in cash.

5.4.3 Behavioral experiment

Even though financial experiments are not yet commonplace in finance, several studies have used such experiments to test for behavioral factors. Bloomfield and Hales (2002) report experimental results that support the Barberis, Shleifer, and Vishny (1998) model

[18] Another party that is present in this market are institutions that are legally restricted from investing in shares. These parties use RCs as a means to circumvent this type of regulation.

of investor sentiment. Deaves, Lüders, and Luo (2005) use a financial experiment to test whether high levels of overconfidence lead to increased trading activity. Bloomfield and O'Hara (2000) use a laboratory experiment to investigate whether transparent markets can survive the competition from less transparent markets and find that most dealers prefer to be of lower transparency if they are allowed to do so. Weber, Keppe, and Meyer-Delius (2000) use experimental markets to test for loss aversion, which is the tendency for individuals to weigh losses more heavily than gains. In their experiment they find that negatively framed endowment can give different market prices than a positively framed endowment. This can be interpreted as evidence for loss aversion. Gneezy, Kapteyn, and Potters (2003) use a financial experiment to test for myopic loss aversion. This combines elements of two behavioral concepts: loss aversion and myopia. Myopia refers to the fact that the evaluation frequency determines the way individuals look at risks. A higher evaluation frequency leads to a higher perception of risk. In their experiment Gneezy, Kapteyn, and Potters (2003) find that more information and more flexibility result in less risk taking. They also find that market prices of risky assets are significantly higher if feedback frequency and decision flexibility are reduced. Both results are in line with myopic loss aversion.[19] The experiment in this study is meant to test for two other behavioral factors, i.e. framing and cognitive errors.

In the experiment we ask the participants to determine or "guess" the fair value of a financial product. This financial product has similar characteristics as a reverse convertible, but is constructed in such a way that the value can be determined with just pen, paper, and a simple calculator. The experiment was first conducted at Tilburg University in the Netherlands in November 2004. Since we only had 49 participants at this experiment, we decided to do a follow-up experiment at Simon Fraser University (SFU) in Burnaby, Canada in February 2005. In total 54 participants took part in the second experiment. Both experiments were incentive-induced. Participants were rewarded for solving the prices of three financial products. The students in Tilburg could earn a maximum of € 5 for each product, leading to a maximum total payoff of € 15. For each € 1 difference between the student's calculation (or guess) and the model price, 15 Eurocents was deducted from the € 5. At SFU the same numbers were used, but now the answers were referred to as Canadian dollars. The maximum reward at SFU was 8 dollars per product and for each dollar difference an amount of 24 dollar-cents was deducted.[20] Participants in the Tilburg experiment were invited using

[19]The study of Gneezy, Kapteyn, and Potters (2003) builds on previous papers that study myopic loss aversion such as Thaler, Tversky, Kahneman, and Schwartz (1997), and Gneezy and Potters (1997).

[20]The maximum of 8 dollars and the deduction of 24 dollar-cents per dollar difference was in line

an e-mail list that was used for economic experiments at Tilburg University. At SFU we put out advertisements on campus and we advertised on the website of the university, where also other experiments are advertised. Participants were told that they could earn a maximum amount of € 15 in Tilburg or 24 Canadian dollars at SFU. Interested participants could e-mail us. All interested participants were selected. In theory there could have been a problem since the experiment at SFU was a repeat of the Tilburg experiment. However, we made sure as much as possible that there was no information leakage from the Tilburg experiment. Besides that, the SFU-students were not told that the experiment had been done before. On average the Tilburg students earned € 8.50 with the experiment, and the SFU-students earned an average of 12.74 Canadian dollars. This also indicates that an information leakage was very unlikely.[21]

We first collected some demographical characteristics from the participants, such as age and year that they started at the university. The most notable difference between Tilburg and SFU-students was that 33 of the SFU-participants did not attend any finance course, while this was the case for only 8 of the Tilburg participants.[22] After asking about the demographics, the participants were invited to solve the three sequential problems, in which they were asked to determine the fair value of a financial product. The characteristics of this product are that it has a time to maturity of two years. In a year from now, and in two years the investor will receive a fixed amount of cash, denoted as C. This amount could be interpreted as the coupon. After two years, the issuer of the financial product decides whether you will be redeemed with a fixed number of shares, denoted as N, or with a fixed amount of cash, denoted as F. The coupon, as well as the number of shares, and the fixed amount of cash are specified in the problem. Furthermore, it is mentioned that participants will receive the fixed number of shares if the price of the share will drop to level X or rise to level Y. Finally, we provided the participants with the stock price performance over the last 2 years, and we mentioned that in the next two years the stock price will have a value X or Y with certainty. The interest rate is assumed to be zero.

In order to test for framing and cognitive errors, we presented our participants four different framing of the same financial product. In version 1, denoted as Up-Positive, we show an increasing historic price pattern over the last two years, and frame the redemption of the reverse convertible in a positive way as follows ‘You will receive a

with the exchange rate at the time of the experiment: € 1 = 1.6 Canadian dollar.

[21]The Canadian amount is equal to 12.74/1.60 is € 7.96. Thus, on average the SFU-participants earned less than the Tilburg participants.

[22]Other information on the demographical variables is, on request, available from the authors.

fixed amount F in cash if the stock goes up, otherwise you will receive N shares'. In version 2, denoted as Up-Negative, we show an increasing price pattern, but a negative framing for the redemption 'You will receive N shares if the stock price goes down, otherwise you will receive a fixed amount F in cash'. In version 3, denoted as Down-Positive, we show a decreasing price pattern of the underlying stock over the last two years, while the framing of the redemption is positive. Finally, in version 4, denoted as Down-Negative, we show a decreasing price pattern over the last two years, and a negative framing of the redemption. The three sequential problems a participant has to solve are formed in the same way.

We made efforts to present the problems as closely to reality as possible. Therefore we selected actual stocks as underlying values. However, in order to avoid a bias based on both knowledge and rumors on the underlying stocks we decided to use stocks that were traded on the Warsaw Stock Exchange in Poland. The assumption was that the stocks are unknown to students at Tilburg University and at SFU. We believe this assumption to be realistic, since the Warsaw Stock Exchange is small and relatively unknown outside Poland. The particular underlying stocks were selected based on their past performance. For each problem we looked for two stocks that had a similar volatility estimated on the 2-year period preceding the pricing date, and the same price. Based on this historical information we computed two future price levels (when the stock goes up and down). Hence for each problem, two chosen stocks had identical past, present and future information except for the trend, i.e. one stock had an increasing historic pricing pattern and another a decreasing historic pricing pattern. The three problems were different in terms of exercise price: one of the options is in-the-money, one is at-the-money, and one is out-of-the-money. We used prices in Polish Zloty and converted them to Euros based on the exchange rate that was prevailing at the pricing dates. As mentioned before, for the sake of simplicity we used the same numbers in the SFU experiment, but we referred to these as Canadian dollars.

The determined or guessed fair value of the financial product was compared to the theoretical price of this product. In Appendix 5.A we present a version of the experiment as distributed to our participants (except that we only show one problem out of three presented to the participants). The problems in the experiment are constructed in such a way that the fair value is simply the average value of future cash flows. For example, a holder of the financial product described in problem 1 (see Appendix 5.A) will receive at the maturity either € 168 (€ 140 face value and two coupon payments of each € 14) or she will receive € 115.50 (€ 28 from coupon payments and 35 shares at a price of

€ 2.5 each). Note that the holder will receive shares only when the price drops down. Since each of these cash flows are equally probable (i.e., current stock price is equal to the expected value of the future prices) the price of the financial product is equal to the average value of future cash flows, which in this case is € 141.75.

In Table 5.7 we report the outcome of our experiment in case of the four different versions, and the two different locations were we conducted the experiment.

It appears that for the total sample of participants we find, on average, underpricing with respect to the theoretical price of the financial product, varying between -0.55% for the Up-Negative version and -24.43% for the Down-Positive version, where the latter one is statistically significant.[23] However, the Tilburg participants that received the Up version overpriced the product with 4.73% and 9.47%, on average. A striking result is that the presented historical price pattern of the underlying stock significantly affects the pricing of the financial product. Consistent with the existence of cognitive errors, in case an increasing historical price pattern is shown, we find significantly less underpricing than in case a decreasing historical price pattern is shown. For the total sample this difference is about 13.62%, while for the Tilburg participants the difference is even 24.96% and overpricing is found in case of an increasing historical price pattern. Furthermore, a positive way of framing the redemption of the financial product leads to significantly more underpricing than a negative way of framing. This difference is about 9.61% for the total sample of participants.

We also study the existence of cognitive errors using our pricing data. We investigate whether RCs on stocks that went up before the issue are overpriced compared to RCs on stocks that went down before the issue. In order to study this we run a regression for each stock with a constant term and a deterministic trend on the data spanning the two-year period before the pricing date. If the slope coefficient is significant and positive we classify the stock as upward trending. If the coefficient is significant and negative, the stock is classified as downward trending. Stocks with an insignificant trend variable are all excluded in the calculations. In total we have 33 upward trending stocks, 39 downward trending stocks and 4 stocks are excluded because their trend was insignificant. Indeed, we find this difference to be positive but not statistically different from zero (i.e. for the whole sample the RCs with the upward trending underlyings are overpriced by 2.52% and the ones with the downward trending underlyings only by 1.93%). However, this results should be interpreted with caution as the difference is mainly driven by the

[23]Tests are based on the non-parametric Mann-Whitney test that compares means of two independent samples based on ranks.

plain vanilla reverse convertibles, for which we only have a relatively small number of observations available (i.e. 14 upward and 16 downward trending stocks which underly our plain vanilla RCs).

Apparently, the framing of the way the simple financial product will be redeemed and the figure of the historical price pattern of the underlying stock of the product, i.e. cognitive errors, play an important role in the pricing of the simple financial product. Although the simple financial product is not exactly similar to a reverse convertible, our results may shed some light on the ability of the framing of the redemption and the past stock price behavior to affect the pricing of the reverse convertible bonds.

5.5 Summary and Conclusions

The question regarding the deviation of the values of assets from their fundamental levels has gained a lot of interest in finance. Recent increase in the global demand for derivatives has shifted the attention from common stocks to derivatives. In this chapter we focus on one type of derivatives, namely reverse convertibles. These are bonds that give right to a high coupon rate and at maturity the issuer has an option to either redeem the bond at par in cash or to deliver a pre-specified number of common stocks. Therefore, they are in fact a combination of a bond and a written put option. Although, the popularity of reverse convertibles originally started in Europe and Asia, nowadays they are also traded on the American Stock Exchange

We studied the reverse convertibles issued on Amsterdam Stock Exchange between January 1, 1999 and December 31, 2002 for which also long-term call options were outstanding. We choose the Dutch market because in this market the reverse convertibles and the long-term options are popular with the investors. This allows us to price the reverse convertibles as the combination of a bond and a put option.

The results indicate a significant overpricing of plain vanilla reverse convertible bonds but no overpricing of the knock-in RCs. The documented overpricing is confirmed in a model-free analysis and is persistent for approximately one fourth of the lifetime of the reverse convertibles. The lack of arbitrage possibilities shows that the investors are not able to exploit observed overpricing and profit from arbitrage opportunities. This, however, should not stop other market forces from correcting the prices.

In order to examine whether behavioral factors like framing and cognitive errors play a role in the pricing of reverse convertibles, we conducted an experiment in which we asked the participants to price a simple financial product with similar characteristics as a reverse convertible. Our results suggest that the framing of the way the simple financial product will be redeemed and the figure of the historical price pattern of the underlying stock of the product, i.e. cognitive errors, play an important role in the pricing of the simple financial product. Although the simple financial product is not exactly similar to a reverse convertible our results shed some light on the ability of the framing of the redemption and the past stock price behavior to affect the pricing of the reverse convertible bonds.

5.A Experiment

On the following pages version 1 of the experiment is presented as it was carried out in Tilburg, the Netherlands (except that we only show one problem out of three presented to the participants) . Version 2 is the same as version 1, except that in each problem the phrase "After two years, additionally the issuer will give you X shares of ABC company that is listed on a stock exchange, if the price of ABC share will go down to € Y, otherwise you will get € F in cash" is replaced by "After two years, additionally the issuer will give you € F in cash if the price of ABC company that is listed on a stock exchange will go up to € Y, otherwise you will get X shares of ABC company". Version 3 is the same as version 1 except that the graph of the stock price will show a downward trend instead of an upward trend. Version 4 is the same as version 2, except that the graph of the stock price will show a downward trend instead of an upward trend.

The experiment at Simon Fraser University (SFU) in Burnaby, Canada is the same as the experiment at Tilburg University, except that all the amounts are presented in Canadian dollars (the amounts are the same as in Tilburg, except they are now referred to as Canadian dollars). Canadian participants can earn 8 Canadian dollars (instead of € 5) and are punished with a deduction of 24 cents for each dollar difference.

In addition to the problems, we asked the participants a number of demographical questions on e.g. age, gender, the year that they started at the university, and on finance courses that they either follow or that they followed in the past. This list of questions is, on request, available from the authors.

Introduction

Welcome to our experiment. The experiment will last for approximately three quarters of an hour. Please study the instructions of the experiment on your own. If you have any questions please raise your hand. You are not allowed to talk to other participants. The experiment does not require any training in finance or economics. If you follow the instructions carefully, you can earn a considerable amount of money. All the money you earn will be yours to keep and will be paid to you privately and in cash, immediately after the experiment.

The experiment consists of 3 successive problems. In each problem, you have to determine or guess the "fair value" of the financial product that will be presented to you. The "fair value" is the price that investors pay for such products in the market.

In all the experiments we assume that the interest rate is equal to zero. This implies that € 500 today put on a savings account will be worth € 500 in two years. Alternatively, the "fair value" of € 500 to be received in two years is € 500.

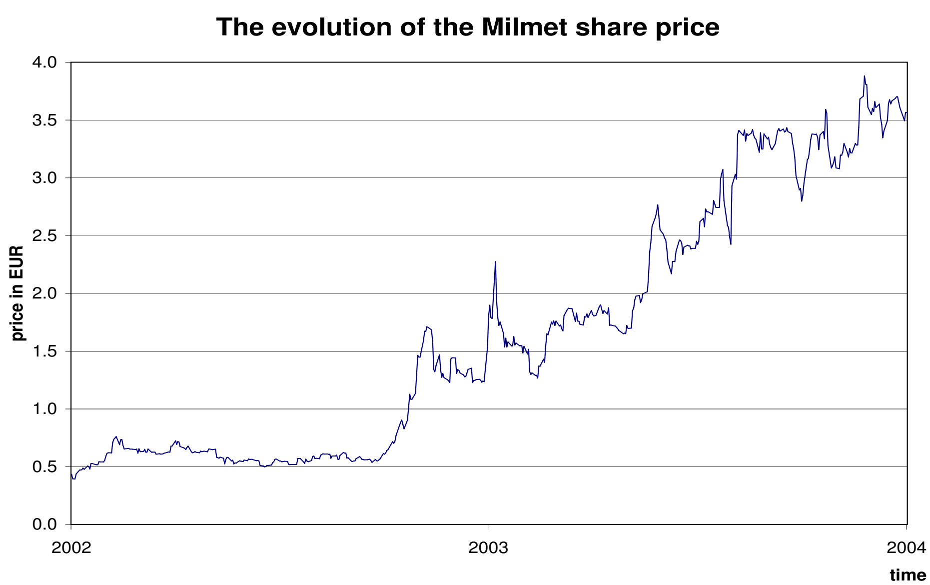
If you determine or guess exactly the fair value, you will receive € 5. For each one-euro difference from the fair value, we will subtract 15 euro-cents from the € 5. However, we will never subtract more than € 5. For example, if the true value was 500 and your guess was 505, then you will receive € 4.25 for this guess.[24] Your final payment will depend on the outcomes of all successive problems and it will be determined at the end of the experiment.

Good luck!

[24]The numbers in this example are arbitrary and should not be taken into consideration in the problems that follow.

Problem 1

What is the fair value that investor should pay in the market for the following financial product:
You keep the product for 2 years
In a year from now and in two years from now you will receive a fixed amount of € 14 each time. This means that in total you will receive an amount of € 28 during this 2-year period.
After two years, additionally the issuer will give you 35 shares of Milmet company that is listed on a stock exchange, if the price of Milmet share will go down to € 2.5, otherwise you will get € 140 in cash.
Assume that the interest rate is zero.
The performance of the Milmet stock over last 2 years is shown on the graph below. The price 2 years ago was € 0.5, the price today is € 3.5 and in 2 years from now it is going to be either € 4.5 or € 2.5.



The fair value is :

5.B. Figures and Tables

Table 5.1: **Summary statistics.**

This table presents a summary of the sample reverse convertibles (RCs) issued on Euronext Amsterdam between January 1, 1999 and December 31, 2002 for which also long-term options were outstanding. A plain vanilla reverse convertible is a bond that at the maturity can be either redeemed in cash or by delivering a pre-specified amount of common stocks. A knock-in RC initially starts as a normal bond. Only when the underlying asset hits the barrier it becomes a reverse convertible. A knock-out RC works in the opposite direction. It starts as a plain vanilla reverse convertible but it turns into a normal bond after the pre-specified barrier has been reached. Panel A presents the overview per issuer and panel B gives the overview of the sample selection procedure.

	Number of Reverse Convertibles			
	Plain Vanilla (1)	*Knock-in* (2)	*Knock-out* (3)	*Total* (4)
		Panel A: Issuer		
ABN AMRO	21	7	5	33
Fortis Bank	3	14		17
ING Bank	16	4		20
Rabo Securities	7	29	2	38
Total	**47**	**54**	**7**	**108**

Panel B: Sample selection

	Original Sample	*No price information in Datastream*	*Less than 5 quoted prices with postive trading volume*	*Final Sample*	*Percentage priced*
Plain Vanilla	**47**	**13**	**2**	**32**	**68%**
ABN AMRO	21	5		16	
Fortis Bank	3	2		1	
ING	16	3	1	12	
Rabo Securities	7	3	1	3	
Knock-in	**54**	**5**	**6**	**43**	**80%**
ABN AMRO	7		1	6	
Fortis Bank	14	1		13	
ING	4			4	
Rabo Securities	29	4	5	20	
Knock-out	**7**		**7**		**0%**
ABN AMRO	5		5		
Fortis Bank					
ING					
Rabo Securities	2		2		
Whole sample	**108**	**18**	**15**	**75**	**70%**

Table 5.2: **Descriptive statistics.**

The sample contains reverse convertibles that were issued on Euronext Amsterdam from January 1, 1999 to December 31, 2002 for which also long-term call options were outstanding. Column (1) gives the size of the sample. Columns (2), (3) and (4) give average, median and standard deviation of the price of reverse convertible per 100 face value. Columns (5) and (6) give average and median of the trading volume of the reverse convertibles. Columns (7) and (8) give average and median of the conversion ratio, which determines the number of shares that may be delivered at redemption of the reverse convertible bond. Columns (9) and (10) give average and median of the barrier level as the percentage of the stock price for the knock-in reverse convertibles. The information on the prices, trading volumes, and the barriers is derived from Datastream.

	Size (1)	Avg Price in % (2)	Med Price in % (3)	Std dev of Price (4)	Avg TV in thousands (5)	Med TV in thousands (6)	Avg CR (7)	Med CR (8)	Avg Barrier as % of stock price (9)	Med Barrier as % of stock price (10)
Plain Vanilla	32	102.92	101.58	4	191673	106000	85.09	72.97		
Knock in	43	98.16	100.54	10	233381	95000	81.25	59.76	78	75
The whole sample	75	100.44	100.18	8	213434	101000	82.89	66.00	78	75

Table 5.3: **Model-based overpricing of the reverse convertible bonds.**

This table presents overpricing of reverse convertible bonds that were issued on Euronext Amsterdam from January 1, 1999 to December 31, 2002 for which also long-term call options were outstanding. The overpricing for each reverse convertible is defined as the difference between the full market price and the model price divided by the model price. This ratio is calculated as the average of the first five trading days. Column (1) gives the size of the sample for each group. Column (2) gives the value of overpricing averaged over reverse convertibles. If the value is positive it means that the reverse convertible is overpriced. The next column, column (3) gives the standard deviation of the overpricing. Columns (4) and (5) report minimum and maximum values in the sample considered. Column (6) presents the median value of overpricing. Finally, column (7) reports the number of reverse convertibles that were overpriced. Panel A gives the results for the Black-Scholes model, and Panel B for the Square Root version of the Constant Elasticity of Variance (CEV) model. Significance levels are based on a two-sided t-test. *** indicates the significance at 1%, ** the significance at 5% and * the significance at 10%.

	Size (1)	*Avg* Overpricing *in %* (2)	*St. dev* (3)	*Min* (4)	*Max* (5)	*Median in %* (6)	*Number of Overpriced* (7)
			Panel A: Black-Scholes model				
Plain Vanilla	32	5.92***	3.46	0.16	13.54	5.63***	32
Knock in	43	-0.62	3.54	-12.72	9.59	-0.37	19
Whole sample	75	2.21***	4.77	-12.72	13.54	1.55***	51
			Panel B: Square Root version of CEV model				
Plain Vanilla	32	5.87***	3.43	0.15	13.42	5.41***	32

Table 5.4: **Model-independent overpricing of reverse convertibles.**

This table presents the overpricing of reverse convertibles that were issued on Euronext Amsterdam from January 1, 1999 to December 31, 2002 for which there are also long-term call options outstanding. The overpricing for each reverse convertible (RC) is defined as the difference between the full market price and the model price divided by the model price. This ratio is calculated as the average of the first five trading days. Column (1) gives the size of the sample for each group. Column (2) gives the value of overpricing averaged over reverse convertible bonds. If the value is positive it means that reverse convertible bond is overpriced. Column (3) gives the standard deviation of the overpricing. Columns (4) and (5) give the minimum and maximum values in the considered sample. Column (6) presents the median value of overpricing. Finally column (7) gives the number of reverse convertibles that are overpriced. Panel A gives the results for those RC for which we were able to identify long-term call options with similar strike price and maturity. Panel B gives the overpricing calculated directly from the call prices using put-call parity. Significance levels are based on a two-sided t-test appropriate for small sample. *** indicates the significance at 1%, ** the significance at 5% and * the significance at 10%.

	Size (1)	*Avg Overpricing in %* (2)	*St. dev* (3)	*Min* (4)	*Max* (5)	*Median in %* (6)	*Number of Overpriced* (7)
		Panel A: The market value of the put premium					
Exactly matched strike	8	4.36***	3.32	-2.27	7.90	4.98***	7
Closely matched strike	10	5.70**	6.62	-7.03	16.05	5.57**	9
All (Plain Vanilla)	18	5.11***	5.31	-7.03	16.05	5.05***	16
		Panel B: Using put-call parity					
Plain Vanilla	32	7.25***	6.11	-1.18	25.50	5.95***	29

Table 5.5: **Threshold value of a discount rate.**

This table presents the average threshold value of the discount rate for which the model-independent overpricing of plain vanilla reverse convertibles is zero. The overpricing for each reverse convertible (RC) is defined as the difference between the full market price and the model price divided by the model price. This ratio is calculated as the average of the first five trading days. Panel A gives the results for the market value of the put premium, Panel B for the case when put value is derived through the put-call parity and Panel C gives the average values in our sample of both the discount rate and the risk-free rate.

	Number of obs (1)	Discount rate (2)
Panel A: The market value of the put premium		
Exactly matched strike	8	2.24%
Closely matched strike	10	2.51% a
All (Plain Vanilla)	18	2.37%
Panel B: Using put-call parity		
Plain Vanilla	32	2.03% b
Panel C: Average values in our sample		
Discount rate		4.71%
Risk-free rate		4.39%

a Two RCs remain overpriced with a discount rate of 10 bp
b Six RCs remain overpriced with a discount rate of 10 bp

Table 5.6: **Average overpricing across calendar time.**

This table presents the annual overpricing of plain vanilla reverse convertibles (RCs) that were issued on Euronext Amsterdam from January 1, 1999 to December 31, 2002 for which also long-term call options were outstanding. The overpricing for each reverse convertible is defined as the difference between the full market price and the model price divided by the model price. This ratio is calculated as the average of the first five trading days. Significance levels are calculated using a two-sided t-test. *** indicates the significance at 1%, ** the significance at 5% and * the significance at 10%.

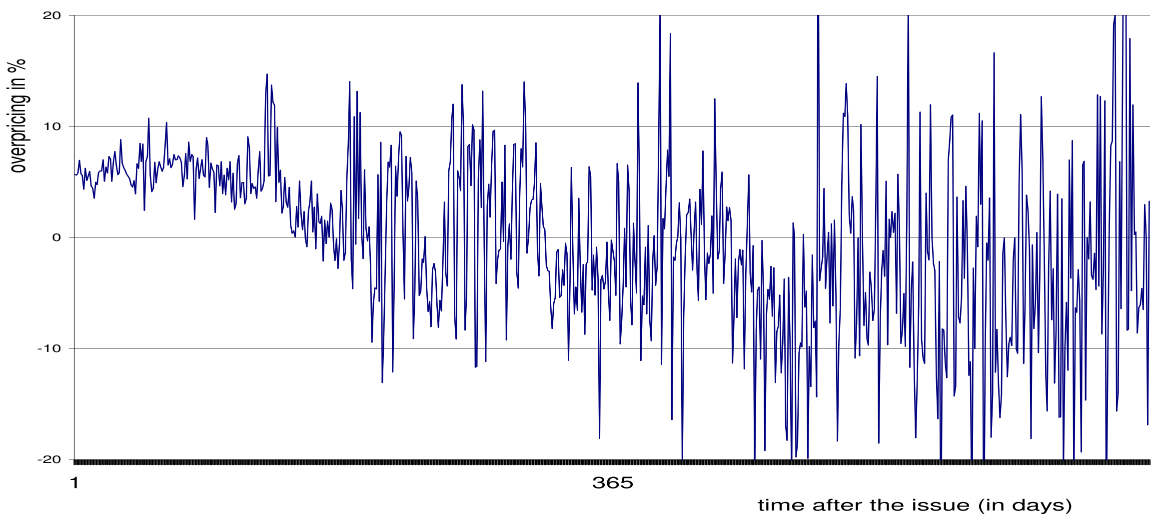
Year (1)	Number of obs (2)	Avg Overpricng in % (3)	Std. Error (4)	t-Statistic (5)	p-values (6)
1999	7	5.05*	6.02	2.22	0.06
2000	14	0.89	4.66	0.71	0.49
2001	21	3.13***	4.37	3.28	0.00
2002	32	1.55*	4.64	1.89	0.06

Table 5.7: **Financial Experiment.**

This table presents the average overpricing of a financial product with similar characteristics as reverse convertibles. Past Info reflects whether the historical price pattern of the underlying stock went Up or Down, while Frame reflects whether we present the redemption of the reverse convertible in a Negative or Positive frame. The overpricing is calculated as the percentage difference between the theoretical price of the product and the determined or guessed value of the product. Columns (1) and (2) give the means, medians and standard deviations for four different representations of the financial product, while columns (3) and (4) give the results of the tests of the differences between these representations. Significance levels are calculated using a two-sided t-test (columns (1) and (2)), and non-parametric Mann-Whitney test (columns (3) and (4)). *** indicates the significance at 1%, ** the significance at 5% and * the significance at 10%.

			Frame			Difference	
			Negative (1)	Positive (2)		Pos - Neg (3)	Up - Down (4)
			Panel A: Tilburg University and Simon Fraser University				
Past Info		Mean	-0.55	-1.88	Difference	-9.61*	13.62**
	Up	St dev	3.53	4.47	in means		
		t-stat	-0.16	-0.42	Mann-Whitney	-1.91	2.08
		Mean	-4.95	-24.43***	z-ratio		
	Down	St dev	6.64	5.43	p-values	0.06	0.04
		t-stat	-0.75	-4.5			
			Panel B: Tilburg University				
Past Info		Mean	4.73***	9.47	Difference	-5.75	24.96**
	Up	St dev	2.33	8.51	in means		
		t-stat	2.03	1.11	Mann-Whitney	-0.76	2.01
		Mean	-8.87**	-27.66***	z-ratio		
	Down	St dev	5.3	9.14	p-values	0.45	0.04
		t-stat	-1.67	-3.03			
			Panel C: Simon Fraser University				
Past Info		Mean	-6.28	-11.11***	Difference	-12.49	3.22
	Up	St dev	6.82	3.83	in means		
		t-stat	-0.92	-2.9	Mann-Whitney	-1.36	0.99
		Mean	-1.02	-21.89***	z-ratio		
	Down	St dev	12.23	6.59	p-values	0.17	0.32
		t-stat	-0.08	-3.32			

Figure 5.1: **Average Overpricing of the plain vanilla reverse convertible bonds.** This figure presents the average overpricing of the plain vanilla reverse convertibles that were issued on Euronext Amsterdam from January 1, 1999 to December 31, 2002 for which also long-term call options were outstanding. The overpricing is defined as the difference between the full market price and the model price divided by the model price. The model price is calculated with the model of Black and Scholes (1973). The average overpricing is calculated at each day between the issuance and maturity of all priced reverse convertibles. The maturity for all reverse convertible bonds is two years (730 days).



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Samenvatting (Dutch Summary)

Deze thesis bestaat uit vier essays met betrekking tot rationele asset pricing. Het eerste essay van deze thesis: *Consumption Risk and Expected Futures Returns*, focust op verwachte rendementen op futures. Rendementen op futures (waarvan de verwachte waarde risicopremies weerspiegelt) zijn relevant zowel voor academici die asset pricing modellen bestuderen als voor praktijkmensen die deze rendementen gebruiken als input voor portfolio- en risicomanagementmodellen e.g. In dit essay bestuderen we meer bepaald de relatie tussen verwachte rendementen op futures en een prijskernel gempliceerd door een consumptie-gebaseerd asset pricing model. Het prijskernel wordt gemeten door de 'intertemporal marginal rate of substitution' (IMRS) van een representatieve investeerder, die enkel functie is van de groei in de geaggregeerde consumptie per capita.

Dit standaard consumptie-gebaseerde model is het best mogelijke raamwerk, althans vanuit een theoretisch standpunt. Vooreerst controleert het voor het intertemporele karakter van de portfoliokeuze (Merton (1973), Breeden (1979)). Ten tweede omvat het impliciet vele vormen van welvaart van een investeerder (niet enkel de welvaart voortvloeiend uit de aandelenmarkt) die relevant zijn om het systematische risico verbonden aan activa te meten (Mankiw and Shapiro (1986), Cochrane (2001)). Ondanks de theoretische aantrekkelijkheid van het consumptie-gebaseerde model zijn empirische studies er niet in geslaagd om dit model toe te passen op een cross-sectie van aandelenreturns (Campbell and Cochrane (2000)). Dit probleem wordt behandeld door een recente stroming in de literatuur, waarin gefocust wordt op de onderliggende assumptie dat investeerders kosteloos hun consumptie kunnen aanpassen (Jagannathan and Wang (2005), Parker and Julliard (2005)). Wij breiden dit onderzoek uit door het toe te passen op een bredere set van activa dan enkel aandelen. We gebruiken futures contracten met als onderliggende activa verschillende grondstoffen (landbouwproducten, vless, energie en waardevolle metalen), munten en een aandelenindex. We bestuderen of excess rendementen op futures contracten systematisch verschillen ten gevolge van verschillen in consumptie-gerelateerd risico gelijkaardig aan het risico op aandelen. Historisch gezien hebben grondstoffenfutures excess rendementen opgebracht gelijkaardig aan deze op aandelen (Gorton and Rouwenhorst (2006)). Deze instrumenten vervullen echter een verschillende economische functie. Daarenboven vormen futures markten een vanzelfsprekende keuze voor het testen van een consumptie-gebaseerd model, vermits de onderliggende grondstoffen sterk gerelateerd zijn tot de geaggregeerde consumptie en kunnen gebruikt worden om het risico verbonden aan consumptie in te dekken.

Onze bevindingen wijzen uit dat het Consumption CAPM 60% van de cross-sectionele variatie in de gemiddelde rendementen op futures kan verklaren. De conditionele versie van het consumptiemodel presteert het best met een horizon van een kwartaal en overklast zowel het CAPM als het Fama-French drie-factor model. We tonen aan dat verwachte futures returns kunnen gemeten worden door de rendementen op futures, en dat het consumptiemodel naast verwachte returns ook in staat is om de cross-sectionele variatie in gemiddelde returns te verklaren. We vinden ook dat het gebruik van de uiteindelijke consumptie (zijnde de som van huidige en toekomstige consumptie) tot een lagere performantie van het model leidt, wat niet overeenstemt met de bevindingen voor aandelenreturns. We tonen aan dat korte-termijn consumptierisico belangrijk is voor grondstoffen ten gevolge van vraag- en aanbodschokken. Lange-termijn consumptierisico is daarentegen niet belangrijk. We vinden dat consumptiebeta's gemeten met betrekking tot de groei in de uiteindelijke consumptie uitdoven tot nul en dat het consumptiemodel dat controleert voor de veranderingen in productie beter in staat is om de cross-sectie van futuresrendementen te verklaren. Dit suggereert dat we voor grondstoffen een directe impact van het aanbod op grondstoffenprijzen en consumptie observeren, die vervolgens leidt tot consumptiebeta's die fluctueren doorheen de tijd. In de mate dat wijzigingen in de grondstoffenprijzen gevolgd worden door wijzigingen in vraag en aanbod kan dit verklaren waarom de uiteindelijke consumptie geen even goede risicomaatstaf is voor grondstoffen als voor aandelen.

Het tweede essay: *An Anatomy of Commodity Futures Returns: Time-varying Risk Premiums and Covariances,* focust op het time-series gedrag van verwachte rendementen op grondstoffenfutures. Eerst ontbinden we de verwachte futures returns in spot en term premies. Deze ontbinding is belangrijk, vermits deze twee risicopremies hoogstwaarschijnlijk verschillende risicofactoren vergoeden (bijvoorbeeld, voor oliefutures weerspiegelt de spot premie het risico in de olieprijs, terwijl de term premie voornamelijk het risico weerspiegelt dat vervat zit in de 'convenience yields'). We tonen aan dat, ondanks het feit dat gemiddelde rendementen op grondstoffenfutures gelijk zijn aan nul, de spot en term premies die er deel van uitmaken tegengestelde tekens hebben en in hoge mate voorspelbaar zijn. We zijn in staat om 30% van de tijdsvariatie in deze risicopremies te voorspellen, waarbij de spot premies meer voorspelbaar zijn dan de term premies. Deze kennis laat investeerders toe om verhandelingsstrategien te ontwerpen gebaseerd op deze verschillende premies en hun voorspelbare variatie.

We confronteren de aangetoonde variatie doorheen de tijd in verwachte rendementen op futures of in risicopremies met drie asset pricing modellen: het CAPM, het Fama-French drie-factor model, en het Consumption CAPM. We vinden dat deze voorspelbaarheid consistent is met het consumptie-gebaseerde CAPM maar niet met het CAPM of met het Fama-French model. In andere woorden, de gedocumenteerde voorspelbaarheid in futures markten is consistent met de blootstelling aan consumptierisico ondervonden door een investeerder die een verhandelingsstrategie toepast die deze voorspelbaarheid uitbuit, maar niet met marktrisico of met de risico's verbonden met de drie factoren in het Fama-French model. Aangezien het risico van een actief in het consumptiemodel bepaald wordt door de covariantie met de consumptiegroei, zou de tijdsvarirende verwachte return moeten voortkomen uit tijdsvarirende conditionele covarianties tussen rendementen op futures en de consumptiegroei, zoals volgt uit Equation (1.2). We vinden inderdaad dat deze covarianties aanzienlijk fluctueren overheen de tijd. Consistent met het Breeden (1980) argument dat de consumptiebeta's van grondstoffen zou kunnen afhangen van hun aanbod- en vraagelasticiteiten vinden we dat de productiegroei een sterkere voorspellende kracht heeft voor de conditionele covarianties dan voor rendementen op futures.

Het derde essay: *Predictability in Industry Returns: Frictions Matter*, focust meer gedetailleerd op de voorspelbaarheid in rendementen op activa en op de relatie tussen deze voorspelbaarheid en asset pricing modellen. Gebaseerd op het werk van Kirby (1998) tonen we aan dat de asset pricing theorie beperkingen oplegt op de hellingscofficinten en R^2s in een voorspellende regressie. In andere woorden, de voorspelbaarheid geobserveerd in de markt is consistent met het systematische risico waaraan een rationele investeerder wordt blootgesteld wanneer hij een verhandelingsstrategie volgt die de voorspelbaarheid uitbuit (de winsten voortvloeiend uit die strategie moeten gelijk zijn aan de risicopremie gempliceerd door het asset pricing model). Het is algemeen aanvaard dat returns in efficinte markten in zekere mate voorspelbaar zijn, maar de vraag of deze voorspelbaarheid al dan niet rationeel is, is nog niet opgelost. Kirby (1998) vindt dat, in een context van frictieloze markten, asset pricing modellen niet in staat zijn om de mate van voorspelbaarheid te genereren die geobserveerd wordt in de markt. Het zou echter wel kunnen dat de in de literatuur gedocumenteerde winsten niet gerealiseerd kunnen worden door investeerders omdat er in de echte wereld imperfecties zijn. De onmogelijkheid om short te gaan of de aanwezigheid van transactiekosten zou investeerders ertoe kunnen brengen om af te wijken van de verhandelingsstrategie uitgestippeld om de voorspelbaarheid in de markt te exploiteren, hetgeen hun winsten kan veranderen. Het is dus belangrijk om deze afwijkingen in overweging te nemen wanneer men de rationaliteit beoordeelt van verhandelingsstrategien die de voorspelbaarheid willen uitbuiten. Dit essay beoogt de impact van marktimperfecties op tests van de consistentie van asset pricing theorien met de geobserveerde voorspelbaarheid in de returns te onderzoeken. We tonen hoe de beperkingen afgeleid door Kirby (1998) veranderen wanneer we marktimperfecties zoals short sales beperkingen en transactiekosten in overweging nemen.

We mogen veronderstellen dat futures markten bijna geen imperfecties vertonen, hetgeen een heel sterke assumptie zou zijn in andere financile markten. We bestuderen de impact van marktimperfecties op het time-series gedrag van returns op activa door sectorportfolio's gecreerd op basis van de aandelen verhandeld in de grote Amerikaanse markten te onderzoeken. We bekomen sterke evidentie voor voorspelbaarheid in de returns op deze sectorportfolio's. Meer bepaald kunnen we tussen 15 en 20 percent van de variantie verklaren. Bovendien vinden we dat investeerders hun investeringsopportuniteiten kunnen uitbreiden door actieve sectorreturns toe te voegen aan de initile set van passieve returns, omdat deze actieve returns hogere Sharpe ratios en hogere risicoaangepaste returns (relatief tot de factormodellen) bieden.

De resultaten suggereren dat men tot incorrecte conclusies kan komen wanneer men geen rekening houdt met marktimperfecties. In frictieloze markten lijkt de geobserveerde voorspelbaarheid van sectorreturns inconsistent te zijn met rationele asset pricing modellen, wat betekent dat investeerders in staat zijn om meer winst te halen uit de voorspelbaarheid dan hun verwachte winst op basis van het risico waaraan ze zijn blootgesteld. We vinden echter dat deze winsten enkel kunnen behaald worden wanneer investeerders kunnen handelen zonder enige transactiekosten. Transactiekosten lager dan 50 basispunten zijn voldoende om een groot stuk van de geobserveerde voorspelbaarheid te compenseren. Bovendien vinden we dat een 'mean-variance' investeerder zijn nutstoename voortvloeiend uit de voorspelbaarheid in returns die niet consistent is met asset pricing modellen significant overschat. Wanneer we marktimperfecties in acht nemen wordt deze winst substantieel gereduceerd.

In het laatste essay van deze thesis: *Behavioral Factors in the Pricing of Financial*

Products, laten we de assumptie van rationele asset pricing vallen. In rationele modellen worden agenten verondersteld hun verwachte nut te maximaliseren met gebruikmaking van identieke overtuigingen over kansverdelingen met betrekking tot toekomstige ontwikkelingen in de economie. Wij laten gedragsafwijkingen van de kant van de investeerder toe die deze assumptie zouden kunnen schaden.

In het laatste hoofdstuk laten we deze gedragsafwijkingen toe om de mispricing te verklaren die geobserveerd wordt in een bepaalde klasse van financile instrumenten, zijnde reverse convertible bonds. Dit zijn obligaties die hoge coupons met zich meedragen. In ruil heeft de emittent de optie om de obligaties op hun vervaldag ofwel in cash ofwel onder de vorm van een vooraf-gespecificeerd aantal aandelen terug te betalen. Reverse convertibles worden meestal gekocht door individuele investeerders die zich niet bewust zijn van de opties, die de obligaties normalerwijze in hun portfolio's houden en niet verhandelen op de aandelenmarkt, en die dus meer vatbaar zouden kunnen zijn voor gedragsafwijkingen (zijnde gedrag dat afwijkt van de veronderstellingen gemaakt door rationele asset pricing modellen). We vinden dat de klassieke RCs gemiddeld 6% overprijsd zijn, maar dat de knock-in RCs juist geprijsd zijn. De geobserveerde overpricing lijkt gedreven te worden door de optiecomponent. Deze waarneming wordt bevestigd in een analyse zonder model en is persistent over een vierde van de levensduur van de reverse convertibles. Daarenboven blijft de overpricing significant in elk jaar van onze onderzoeksperiode. Aangezien het aantal uitgiftes stijgt overheen de onderzoeksperiode geeft dit aan dat investeerders substantile verliezen incasseren in deze markt. Met behulp van een financieel experiment waarin we de participanten vragen om een simpel financieel product met gelijkaardige karakteristieken als een reverse convertible te prijzen gaan we na in welke mate gedragsfactoren zoals framing en cognitieve fouten bijdragen tot de geobserveerde overpricing. Door aan te tonen dat deze factoren belangrijk zijn verkrijgen we het inzicht dat rationele factoren alleen niet in staat zijn om de overpricing te verklaren. Een dergelijke aanpak omzeilt de moeilijkheid (of zelfs de onmogelijkheid) om alle mogelijke rationele verklaringen op te sommen. We vinden dat framing en cognitieve fouten een belangrijke rol spelen in het prijzen van een eenvoudig financieel product. Hoewel dit product niet exact gelijk is aan een reverse convertible bieden onze resultaten een inzicht in de impact van framing van de terugbetaling en van het voorbije aandelenkoersgedrag op de prijs van reverse convertible bonds.